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## Uncertainty in Flood Risk and its Implications for Management

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Department of Geography

# Uncertainty in Flood Risk and its Implications for Management

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## Abstract

Flooding in the UK is one of the mostly costly natural hazards. Reliable estimation of flood risk is becoming increasingly relevant to flood management practices as the insurance industry, planning decisions and allocation of flood resources are encouraged to move towards a fully risk-based methodology.

This thesis describes the implementation of a flood modelling chain to estimate the flood risk and quantify the associated uncertainty for the city of Carlisle, UK. Observational data from an extreme flood in January, 2005 is analysed to estimate its accuracy, then a method of reducing inconsistencies in the measurements is proposed. The observational dataset is used to condition a hydraulic flood model for the area. The potential benefit of implementing risk-based calibration schemes as an alternative to a global scheme that gives equal weight to all observations is investigated and found to be minimal in this instance.

A flood frequency curve for peak flood discharges in Carlisle is derived using a Bayesian statistical model that combines estimates of historic floods with systematic river gauge data. The uncertainty in the resulting flood frequency curve reflects errors in estimates of peak flood discharge, changes in the channel and floodplain as well as the uncertainty arising from the limited length of the gauge data and compares favourably against the current 'best practice' methods.

The flood frequency curve is used to drive the hydraulic model in a series of Monte Carlo simulations to give probabilistic maps of design floods for Carlisle. Spatial dependence between river flows and variability in flood hydrographs are incorporated in the Monte Carlos simulations. The uncertain consequences of the floods are examined in terms of financial risk, and risk to population and property.

A social research project using semi-structured interviews attempts to establish the relevance of the results to urban planning, the insurance industry and flood management resource allocation. Discussion of uncertainty in flood risk in a broad context suggests a high level of awareness, but not prioritisation with no accepted standard of communication.

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## Chapter 1. Introduction

### 1.1 Flooding in Ruthin, North Wales, 2012

At 06.30 GMT on 27 November 2012 the residents of the Glasdir housing estate in Ruthin, North Wales were awakened by a team of 7 postmen who had noticed that the water level of the nearby River Clwyd was dangerously high, and rising (BBC News Wales, 2012a). By 07.30 GMT the estate was flooded affecting 122 residential properties on the Glasdir estate (Denbighshire Free Press, 2012). Ruthin was not the only town affected by floods in North Wales at the time. Indeed the heavy rain of the preceding 3 days caused the most damage further north in St Asaph (BBC News Wales, 2012b). Elsewhere in Britain the Environment Agency had issued 185 flood warnings with inundation reported in areas as far afield as Cornwall and Devon in the South to Yorkshire in the North (BBC News, 2012). What makes the Glasdir estate an interesting case that bears further scrutiny is that it is a recent development, with construction of some parts still incomplete at the time of the floods. So, given that flooding is known to be one of Britain's most costly natural hazards (Brown and Damery, 2002), how could this development have been given permission to go ahead on a floodplain? What did the residents know about the flood risk to their homes when they decided to buy there? What was the cause of the flooding? What is the impact of the flood on the house prices and insurance costs for the residents? In seeking to answer these questions for the case of the Glasdir estate floods we can see how not addressing and communicating uncertainty in flood risk might lead to disastrous consequences for residents.



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Figure 1.1. Flooding of the Glasdir estate, Ruthin, North Wales. 27 November 2012 (from BBC News Wales, 2012b). © BBC 2012.

#### 1.1.1 Background to the Glasdir estate development

There was certainly no illusion that the proposed development at Glasir was not on the floodplain of the River Clwyd. The Strategic Flood Consequence Report prepared by JBA consulting in 2007 specifically mentions this fact (JBA Consulting, 2007), figure 1.2 shows how the area is roughly bisected by the medium risk zone (between 0.1 and 1% annual chance of flooding) (JBA Consulting, 2007) as identified by the Environment Agency's EFO maps (see Environment Agency, 2011b). However, the land at Glasdir had been identified by the Welsh Development Agency as a strategic site for housing development (North Wales Daily Post, 2012) so it seems the council was keen that a construction company was found to develop the site.

In 2006 Taylor Woodrow Developments was granted permission to build the initial phase of the 178 dwelling estate (Denbighshire County Council Planning Committee, 2006). A flood risk assessment had been carried out (Denbighshire County Council, 2005) with the result that a flood bund had to be created on the eastern boundary of the site and the properties deemed to be within zone 2 (the 0.1% annual flood risk) should have finished floor levels raised 200 mm above the flood levels of the 0.1% AEP flood (Denbighshire County Council, 2005). This was on top of an alleviation scheme

built in 2003 to address repeated flooding in the area by creating a bypass channel to divert water away from the town of Ruthin and the plot that would become the Glasdir estate (BBC News Wales, 2004).

In addition it was acknowledged that a link road constructed to give access to the development crossed the floodplain on an embankment thus affecting the natural storage capacity of the floodplain. As a result the road embankment was designed with culverts to convey the floodwaters downstream (Venables, 2013). The development was given permission to go ahead on the basis of these conditions being fulfilled (Denbighshire County Council, 2005).

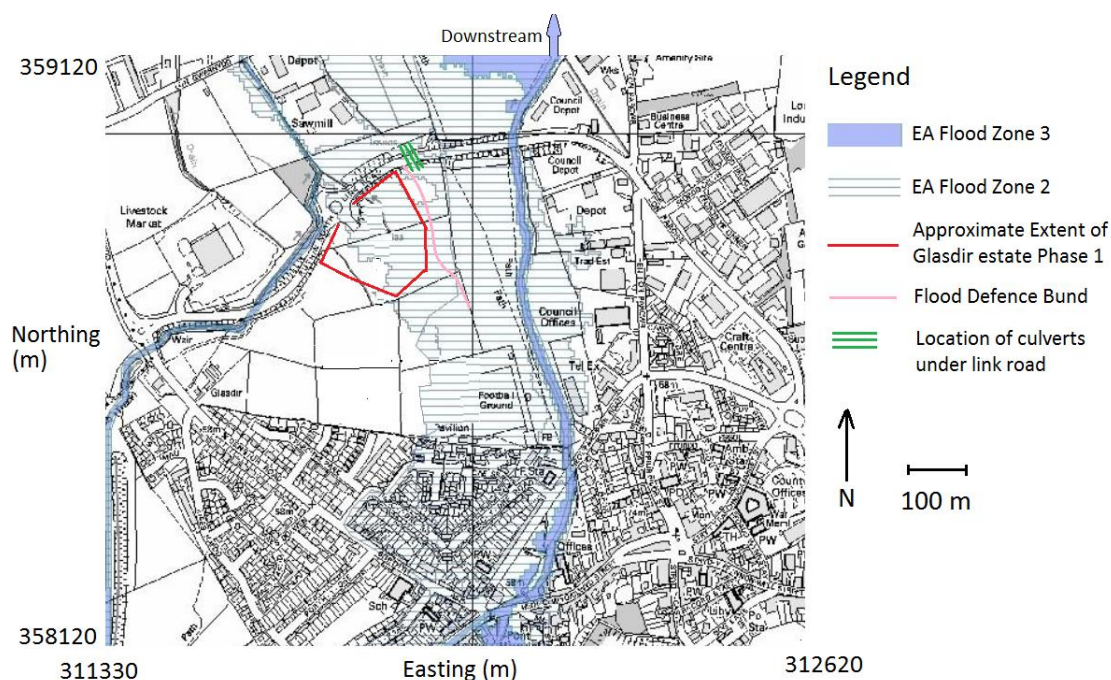


Figure 1.2. Location map of Ruthin, Denbighshire, North Wales showing location of Glasdir estate development and the flood risk zones as defined by the Environment Agency at the time of the flooding (27 November 2012). The flood risk zones have subsequently been revised for this area. Environment Agency Copyright and/or database rights 2009. © Crown copyright and database right. All rights reserved.

Buyers of the brand new homes in the Glasdir estate were assured that the defences in place would protect them from a one in a 1,000 year flood (Wales Online, 2012a) with written assurance from the Environment Agency that the area was safe from flooding (The Telegraph, 2012). It seems the buyers went ahead on the basis that

the risk of their new homes being flooded in any year was less than one in one thousand.

### 1.1.2 Causes of the flooding on 27 November 2012

One possible explanation for extent of the flood water was that the event really was extreme and exceeded the one in one thousand year flood as defined by the flood frequency analysis for Ruthin. But this scenario was ruled out by the Environment Agency Wales, who estimated the return period to be less than one in 200 years (Environment Agency Wales, 2012) – severe, but not enough to damage properties protected beyond one in one thousand years.

In the final analysis the most significant factor identified by the investigations following the event was the extent to which the culverts under the link road were blocked by debris and vegetation thus preventing water flowing to the floodplain on the northern side of the road (Venables, 2013). Witnesses who saw the state of the screens covering the culverts and hydraulic modelling of the event suggest that the culverts were at least two thirds blocked resulting in significantly higher water levels on the upstream side of the link road than the downstream side (Venables, 2013). This pooling of water was enough to overwhelm the earth flood defence bund and flow into almost all the houses in the Glasdir estate – even those beyond the area defined as at risk of a one in one thousand year flood.

Whilst this explanation for the damaging flood isn't in doubt, debate continues over who was responsible for maintaining the culverts (Wales Online, 2012a; Wales Online, 2012b) and why screens so susceptible to blockage were installed in the first place (Venables, 2013), the dispute inevitably leading to legal action (BBC News, 2013).

As well as the stress, inconvenience and sheer hard work faced by the residents in the immediate aftermath of the flood, they are now faced with a longer term financial double impact of large reduction in house prices leaving residents in negative equity and a considerable rise in insurance costs, which may be unaffordable to some.

## 1.2 Thesis Aims

It would seem that the uncertainty in the flood risk estimates, from the hydraulic modelling of the site, to the impacts of the various land-use changes, the flood frequency analysis of the River Clwyd and the possibility of flood defence asset failure was not addressed and was certainly not communicated to the residents and potential house buyers on the Glasdir estate. This thesis expands on these critical themes behind flood risk assessment showing how incidents such as the Glasdir estate flooding are likely to continue unless greater account is taken of fluvial flood risk uncertainty.

Briefly, the aim of this thesis is to *present a method for quantifying the uncertainty in areas of flood risk and to explore the implications of uncertainty for flood risk management*. The hypothesis of this PhD project is that uncertainty in flood risk is highly consequential to planning decisions, the pricing or availability of home insurance and the allocation of resources for flood mitigation projects, but is often ignored or is not communicated fully and effectively. Building on the published literature in the subject areas, this thesis proposes a new method for quantifying the uncertainty in flood risk that encourages exploitation of the limited data available in a necessarily subjective way. Furthermore, by augmenting the physical science with social research, the method will have been exposed to a variety of stakeholders. This helps to establish the worth of the techniques beyond the immediate scientific community and place them in the context of issues facing practitioners in general when attempting to take account of uncertainty in flood risk management.

The sources of uncertainty when estimating flood risk are many and varied and the canon of published literature on the subject extends beyond journal articles to entire academic books (for example Beven and Hall, 2014). However it would be misleading to describe uncertainty in flood risk to be a mature subject; the techniques and methodologies are very much in development with active debate as to the suitability of contrasting approaches (see for example Beven et al., 2007b; Mantovan and Todini, 2006). It is not the aim of this thesis to attempt to develop a framework that can account for every source of uncertainty that may significantly influence flood risk estimates in Carlisle. Instead a selective approach is taken that strives to make optimal

use of the available data for the case study but in a way that is transparent with respect to its limitations.

### 1.2.1 Thesis objectives

The thesis aim to *present a method for quantifying the uncertainty in areas of flood risk and to explore the implications of uncertainty for flood risk management* is achieved through the following objectives:

1. *Estimate and minimise the uncertainty of observational data of the January 2005 flood in Carlisle.*

The observational data of the January 2005 are essential to calibrate the hydraulic flood model of the event. The rarity of the existence of point observations of peak flood extent and depth means that techniques for analysing the accuracy of observational datasets such as that collected after the Carlisle flood are relatively undeveloped.

2. *Build a hydraulic model of the case study flood event and calibrate it against the uncertain observational data available.*

A hydraulic flood simulation of the January, 2005 Carlisle flood is used as the basis for estimating the extent of design floods in Carlisle.

3. *Estimate the flood frequency curve for the study event with minimised uncertainty.*

Flood frequency curves describe the relationship between the peak discharge and probability (return period) of a flood. The peak discharge of a flood event is a key metric used to characterise the severity of a flood, but the river gauge data needed to estimate flood frequency curves at a location of interest is always limited and error prone or may not exist at all.

4. *Run the design flood simulations using the results of the entire modelling chain and assess the consequences.*

Using the hydraulic model and flood frequency curve from objectives 2 and 3 to produce probabilistic maps of the 0.01 AEP design floods in Carlisle and estimate the consequences, with confidence intervals in terms of the numbers of properties at risk, risk to population and financial risk. This achieves the

primary aim of the thesis to “*present a method for quantifying the uncertainty in areas of flood risk*” for Carlisle.

5. *Assess the relevance of the results in the wider context of governance by investigating the importance of and methods employed in the management of uncertainty when assessing fluvial flood risk.*

It is beneficial to establish the context of the results of the physical science research by establishing its relevance to flood risk management beyond academia. Quantified flood risk plays a key role in three specific areas of governance:

- Insurance, where the market is moving to a more risk based approach to pricing and the industry is facing tighter solvency regulation requiring calculations of value at risk up to a 200 year return period (European Commission, 2009a).
- Land use regulation. Planning policy dictates the preparation of flood risk assessments for all proposed developments that assess the level of flood risk and define requirements for the development to mitigate the risk.
- Allocation of funding to and prioritisation of flood and coastal erosion risk management (FCERM) projects. Proposed projects are appraised on the benefits they bring by reducing the consequences of flooding.

### 1.3 Thesis Structure

The UK city of Carlisle, Cumbria was affected by a devastating flood in January 2005. This city and flood event are used as a case study around which to build a modelling chain to give quantified uncertainty bounds for estimates of flood risk of the sort that are crucial to policy makers and practitioners. To that end, four of the core chapters in the thesis are given over to advancing the physical science of flood modelling and frequency estimation, with the final core chapter summarising the findings from a series of interviews with stakeholders from a wide range of organisations concerned with flood risk management. Figure 1.3 shows how the sections in the modelling chain relate to the chapters in the thesis.

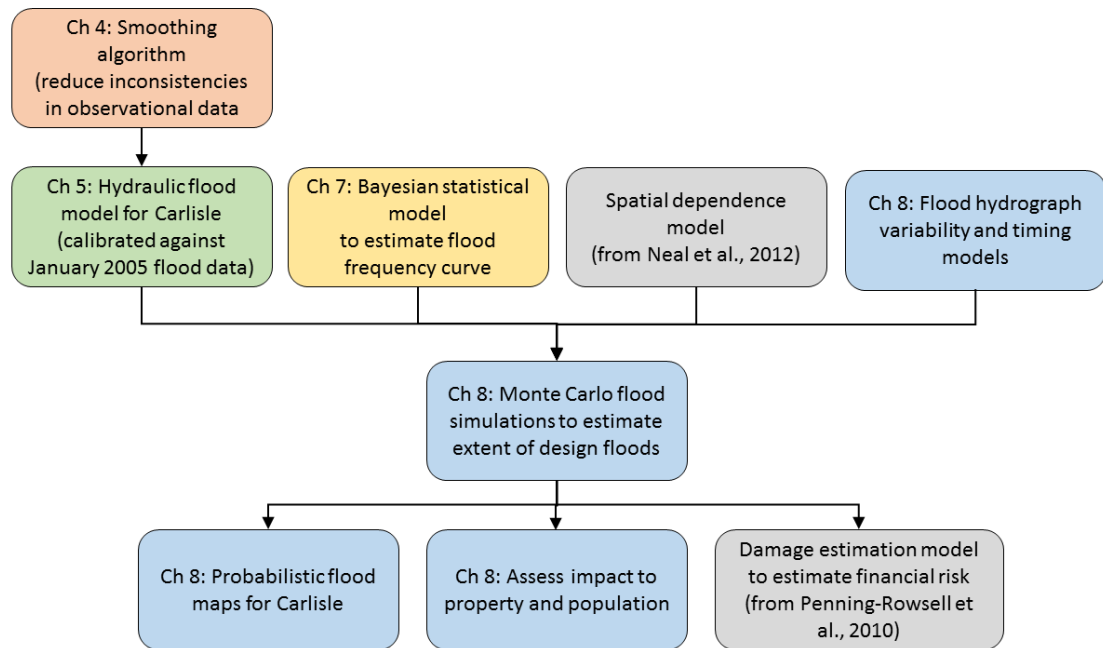


Figure 1.3. The modelling chain developed to estimate the uncertainty in design floods in Carlisle, UK. The colours of the boxes represent the thesis chapters where the models are described; grey boxes indicate the use of third party models<sup>1</sup>.

The core chapters in this thesis are split into three parts. After this introduction and a chapter covering the data and methods used in the research, **part 1** (chapters 3 to 6) covers the process of setting up and calibrating a hydraulic flood model. Next, **part 2** is concerned with flood frequency estimation. **Part 3** combines the results from the previous parts to quantify the uncertainty in design floods and examine the implications of this for governance. The chapter structure is as follows:

Chapter 1. Introduction

Chapter 2. Data and methods

Introduces the Carlisle case study and all the associated datasets. Describes the flood modelling software, statistical methods employed for flood frequency analysis and the set up of Monte Carlo simulations.

Part 1. FLOOD MODELLING

Chapter 3. Review of flood modelling and uncertainty

<sup>1</sup> Chapter 6 is not included in figure 1.3 because it is a literature review chapter.

Literature review providing background on environmental modelling in general and hydraulic flood modelling. Focus on methods developed to manage the intrinsic uncertainty in the modelling process.

#### Chapter 4. Uncertainty in point observations

Comprises, firstly a numerical estimation of the accuracy of the measurement data of the Carlisle 2005 flood and secondly a proposal for a new data smoothing technique aimed at reducing the overall uncertainty in this and similar datasets. This chapter takes the form of a published journal article (Parkes et al., 2013). Emphasises the subjective nature of the choices laid to the practitioner when attempting to minimise uncertainty in the face of limited data.

#### Chapter 5. Flood model structure and calibration

Describes the process of setting up and calibrating models that simulate the Carlisle 2005 flood. Initially using a simple 1-D model to provide a benchmark for evaluating subsequent 1-D/2-D model simulations using LISFLOOD-FP (Bates and De Roo, 2000). Model sensitivity is examined, then the generalised likelihood uncertainty estimation (GLUE) methodology of Beven and Binley (1992) is used to identify a behavioural model parameter set encapsulating the uncertainty in the modelling process. As well as applying global measures of model evaluation, several subjective evaluation schemes are also defined in order to implement a 'risk-based' calibration scheme aimed at optimising model performance in areas where the consequences of flooding are greatest as proposed by Pappenberger et al. (2007b).

### Part 2. FLOOD FREQUENCY ANALYSIS

#### Chapter 6. Review of flood frequency analysis

A second literature review chapter dedicated to the extensive subject of flood frequency analysis within the field of extreme value statistics. Concentrating on the flood frequency methods applied in the UK.



## Chapter 7. Estimating flood frequencies in Carlisle

Describes the design and implementation of the Bayesian statistical model used to estimate a flood frequency curve for Carlisle that makes use of systematic data from a river gauge and highly uncertain historical flood estimates from the city. A subjective use of all available data is required to take account of the maximum number of sources of uncertainty. Similar methods using Bayesian techniques have been used for several locations worldwide (for example Kuczera, 1999; Reis and Stedinger, 2005; Viglione et al., 2013). It is thought that this is the first time a Bayesian statistical model of this kind has been implemented for flood frequency analysis of a river in the UK, where historical data has been used, but not combined with systematic data using Bayesian methods (Archer et al., 2007a; Macdonald and Black, 2010; MacDonald et al., 2013; Macdonald et al., 2006). Compares the results of the model with that produced by commercial software package recommended for use in the UK by the Environment Agency.

## Part 3. UNCERTAINTIES IN DESIGN FLOODS AND THEIR IMPLICATIONS FOR MANAGEMENT

### Chapter 8. Simulating design floods in Carlisle

Flood hydrographs are generated to match the flood frequency curves from chapter 7 taking account of spatial dependence and hydrograph variability. The hydrographs are used with the hydraulic model set up from chapter 5 in a Monte Carlo simulation to produce 200 sets of 1,000 years of simulated flooding in Carlisle. The results are used to produce probabilistic flood risk maps indicative of the 'design floods' relevant to the planning and insurance industries (Christian et al., 2013; Di Baldassarre et al., 2010). The uncertain consequences of such floods are assessed in terms of population, property and financial risk and proper consideration is given in to the full breadth of relevant uncertainties, many of which have not been included in this project

### Chapter 9. Implications of flood risk uncertainty for governance

Attempts to place the physical science of the previous three chapters in context by discussing the approach with various stakeholders from organisations involved in flood risk management. This chapter highlights the issues, not just of quantifying and communicating uncertainty, but also the difficulty of raising its priority against competing activities for the policy makers, companies and NGO's. Beyond that chapter 9 includes a wider discussion of communicating uncertainty on flood maps and the extent to which the wider public appreciate the concepts of risk and uncertainty.

## Chapter 10. Conclusion

## Chapter 2. Data and Methods

This chapter explains the choice of Carlisle in the UK as the case study site for the thesis. As well as providing some brief background information of the geography and history of Carlisle, the meteorology and events of the January 2005 flood are described.

In the subsequent ‘core’ chapters that make up this PhD thesis there are numerous references to various sources of data. These include scientific data collected by the Environment Agency, the Met Office or research scientists as well as less official sources of information useful for flood risk analysis such as newspaper archives, historical images and epigraphic markings. The data sources and the ways they are utilised are described in some detail here to provide context for their subsequent use in the various models developed for this research project.

The chapter is structured as follows. First the Carlisle case study is introduced (section 2.2) and background on the history and geography of the city is given in section 2.3. Sections 2.4 and 2.5 describe the meteorology leading to and the effects of the flood respectively. The following 4 sections (2.6 to 2.9) give details of the various data sets including historical flood records that are required to run and calibrate the flood models and derive a flood frequency curve for the River Eden at Carlisle. Sections 2.10 and 2.11 briefly describe the methods used to produce flood frequency curves and models of design floods with associated uncertainty. Section 2.12 lists the sources of data and the methods employed to enumerate the consequences of the simulated flood events from various different aspects. Finally, section 2.13 is a brief description of the social research methods used for chapter 9.

### 2.2 Carlisle case study

The selection of the case study for this project was far from straightforward. The participatory approach meant that floods outside the UK were not considered for purely logistical reasons, but that still left many UK events in recent decades from which to choose. The quality of the available data for the flood event was the decisive factor: in order to calibrate a flood model it is desirable to have access to good quality

observational data of a previous flood event, time series measurements of river discharge and an accurate 3-D digital elevation model (DEM) of the flood plain.

The most damaging flooding to affect the UK in recent decades occurred in the summer of 2007 (Penning-Rowsell, 2015), when many towns along the lower Severn river were inundated (Marsh and Hannaford, 2007). Tewkesbury, situated at the confluence of the Rivers Severn and Avon was particularly badly affected on 21<sup>st</sup> July 2007 with 1500 homes flooded (Mason et al., 2008) and considerable flooding in the rural areas surrounding the town (Neal et al., 2011). There are sets of aerial photographs available from 24<sup>th</sup>, 27<sup>th</sup> and 31<sup>st</sup> July 2007 as well as a TerraSAR-X stripmap image acquired on 25<sup>th</sup> July (Mason et al., 2009). There is also a 2m resolution gridded LiDAR based digital surface model (DSM) of the town and surrounding area with a 0.103 RMSE vertical accuracy over hard surfaces (Neal et al., 2011).

The quality of observational data and availability of a high resolution DSM suggested the flood event might be an ideal case study for this project. But the great extent of the flooding in the area (see figure 1 in Mason et al., 2010) meant it was difficult to construct a flood model of a resolution sufficient to simulate urban flooding. The problem was that since the flooding extended for many miles downstream from Tewkesbury, when modelling an area of approximately 7 km<sup>2</sup> around the town, the downstream boundary condition for the flood model had to have a defined free surface elevation (due to the backwatering from the downstream flooding) rather than allowing free surface flow out of the domain. The downstream water surface elevation was established in part from water level readings from an upstream gauge. This is undesirable because that gauge data would also be needed for model calibration (see Neal et al., 2011 for further discussion). Furthermore, when attempting to calibrate the model, the downstream water level setting was found to have a predominant effect on the model performance. Consequently this event was rejected as a case study in spite of the quality of available data.

The event that was chosen as a suitable case study was a flood that affected Carlisle on 8 January 2005. It was the worst that the city had experienced in over 200 years

(Environment Agency, 2006), with much of the city inundated. Figure 2.1 shows the estimated extent of the flooding and how the topography of the area means the valley of the main river, the Eden, narrows near the downstream boundary edge suggesting an obvious downstream boundary for the model domain. But neither the geography of the city or the severity of the flood was the primary reason this event has been of considerable interest to flood research. Instead it is the unique set of accurate observations of peak flood depth and extent that was collected in the weeks following the flood. The observational data was collected by two separate teams, one from the University of Bristol and another from the Environment Agency both using differential GPS devices accurate to within  $\pm 0.01$  m (Horritt et al., 2010). The resulting 263 observations of flood depth and extent from a mixture of rural and urban locations spanning the 3 main watercourses in Carlisle provide a useful dataset against which to validate the ability of flood models to simulate the maximum extents of the flooding in and around the city. In addition to this dataset, the historic importance of the city means there are several sources of information on historic floods along with time series of flow measurements from several local river gauges operated by the Environment Agency.

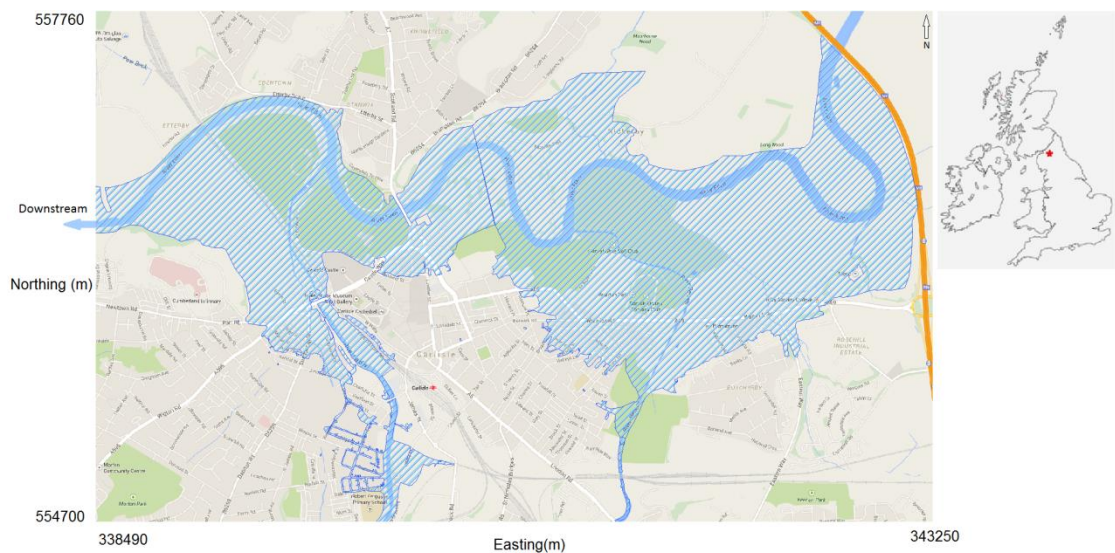


Figure 2.1. Location and map of Carlisle showing estimated extent of the flooding from 8<sup>th</sup> January 2005 (Environment Agency, 2006). Map data © 2014 Google.

## 2.3 Carlisle

Carlisle is a city in Cumbria, North West England with a population of approximately 100,000; it is the largest settlement in the English county of Cumbria. Carlisle is located on the confluence of the rivers Eden, Caldew and Petteril and sits just 16km south of the Scottish border – the reason for the nick name “the Border City” (Visit Cumbria, 2012). It is perhaps due to its strategic position on a river near the coast and close to the border that Carlisle has stood as an important regional settlement for several thousand years.

### 2.3.1 History

The town pre-dated the Roman invasion of Britain and was said by early historians to be one of the strongest British towns prior to the arrival of the Romans (BHO, 2014). The first Roman fort was built near the confluence of the Eden and Caldew rivers in AD 72 and when Hadrian’s Wall was built in the second century AD, the fort was replaced by a larger one housing a regiment of 1,000 soldiers (History of Carlisle, 2012; iRomans, 2012; McCarthy, 2011). The stone castle, city walls and cathedral that all remain to the present day were built in the 12<sup>th</sup> century AD during the rule of Henry I (Lambert, 2012; Visit Cumbria, 2012).

The population of the town grew rapidly during the 19<sup>th</sup> century as many factories and textile mills were built during the industrial revolution (Armstrong, 1981). A lot of the new factories and associated housing were built in the low lying Caldewgate and Denton Holme areas of the Caldew valley (Jones, 2005), with development around the Petteril at Brunton Park and Botcherby following in the late nineteenth and early twentieth century (Smith and Tobin, 1979). The development of areas at risk of flooding from the Eden, Caldew and Petteril has continued to more recent times with the building in the 1960s of an industrial estate at Willow Holme: a location with a known history of recent floods (Smith and Tobin, 1979). The 11-storey Carlisle Civic Centre in Rickergate built in 1964 (Lambert, 2012) which housed the Strategic command centre was flooded in 2005 forcing the police headquarters to temporarily move to Penrith (Environment Agency, 2006).

In the 20<sup>th</sup> century the textile industry that had grown in Carlisle in the nineteenth century declined, however, the strong transport links provided by the railway and the M6 motorway has helped Carlisle retain significant engineering and food manufacturing industries (Discover Carlisle, 2012; Lambert, 2012). Considerable investment was made in the 1980s and 1990s redeveloping the crowded medieval tenements in the city centre with a new shopping centre and pedestrianizing the surrounding streets (Discover Carlisle, 2012).

### 2.3.2 Geography

Carlisle is the county town of Cumbria and the significant urban centre of the wider, local government district of the City of Carlisle (figure 2.2). The population count for City of Carlisle including the non-metropolitan areas was estimated at 107,500 in the 2011 census (ONS, 2011). The main conurbation lies to the south of the River Eden which meanders from East to West on its way to discharging into the Solway Firth approximately 10 km to the north-west. The floodplain of the Eden is largely undeveloped with some sports facilities and a waterworks being the primary land use near the river, although the police station, fire station and city council offices were all positioned on low ground in the centre of town. The main road bridge carries the A7 road over the Eden and connects the suburbs of Belah, Edentown, Stanwix and Knowefield to the north of the river with the main town. Downstream of the A7 bridge is a railway bridge and disused road bridge. Upstream is a minor bridge near the confluence with the River Petteril then the M6 motorway crossing near Linstock.

### 2.3.3 The Rivers Eden, Caldew and Petteril

The catchment area of the River Eden and its tributaries is largely in the English Lake District (see Figure 2.3), a mountainous national park with the highest annual rainfall in England (Barker et al., 2004). The Eden is 130 km long (Eden Rivers Trust, 2011) with a catchment to Carlisle of roughly 2,280 km<sup>2</sup> including the rivers Caldew and Petteril (Spencer et al., 2006). The central valley of the Eden is mainly sandstones and shales, the eastern slope is formed by the steep northern Pennine escarpment and the western watershed forms a large part of the English Lake District (Mayes et al., 2006; Smith and Tobin, 1979). The steep valleys characterising the upper Eden gradually give way to wide flood plains as the river flows downstream to the lower Eden



(Environment Agency, 2009a). Although a lot of the central Eden valley lies in the rain shadow of the mountains of the Lake District (Smith and Tobin, 1979), the higher altitude locations experience very high annual precipitation with averages as much as 2,800 mm (Pattison and Lane, 2011).

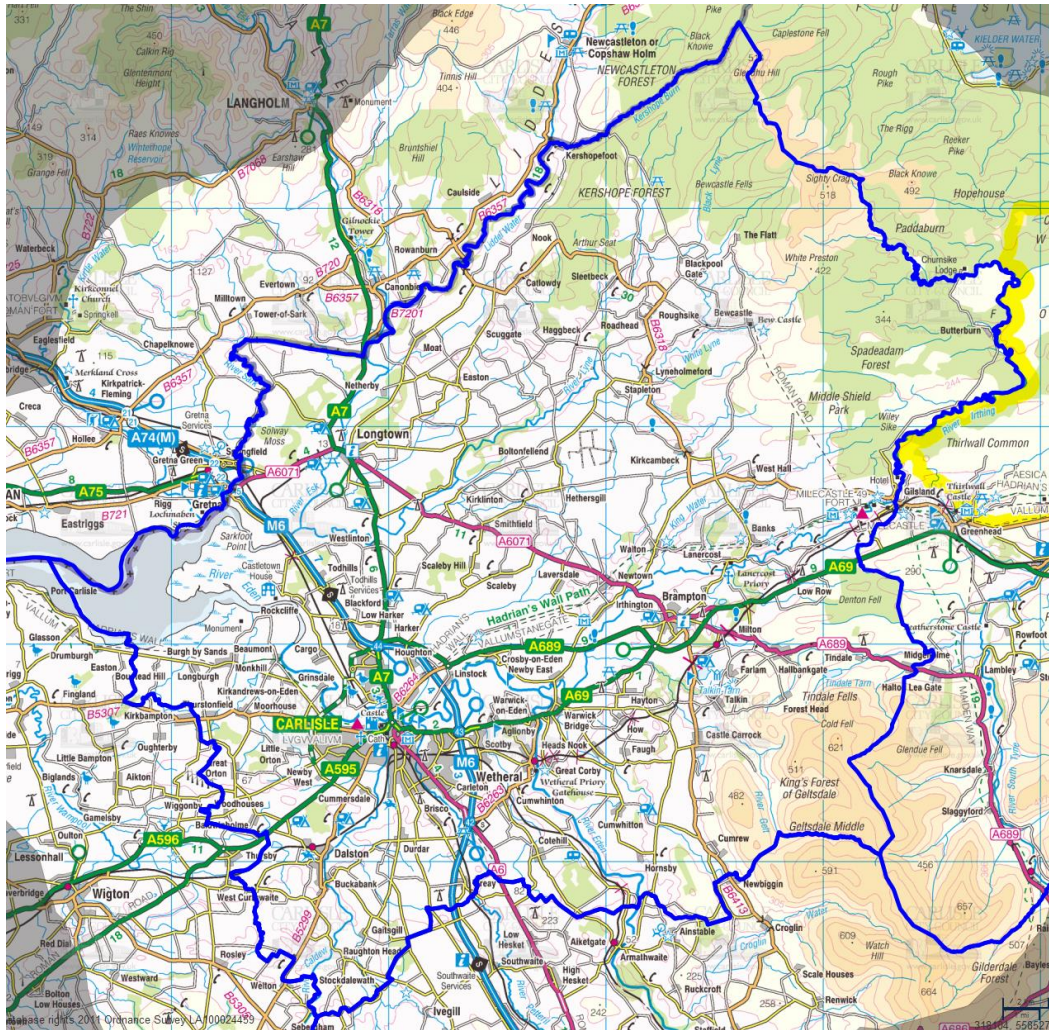


Figure 2.2. Ordnance Survey map of the local government district of the City of Carlisle. © Crown copyright and database rights 2011 Ordnance Survey.

The average annual precipitation across the catchment is 1,183 mm (Pattison and Lane, 2011). The vast majority of the catchment is rural with less than 1% urbanised (Environment Agency, 2009a). Below the steep gradients in the Lake District and the Pennines the land cover is predominantly agricultural; extensive sheep farming in the foothills giving way to intensive, high quality farmland in the Eden valley (Environment





started on 6<sup>th</sup> January 2005 soil moisture deficit values across much of the north of England were low and river levels were generally above average for January (Archer et al., 2007b). On 6<sup>th</sup> January, a very moist and mild tropical air mass originating at low latitudes in the tropics moved east over the UK driven by strong south-westerly winds (Environment Agency, 2006). At this time several low pressure systems lay to the north-west of the UK over Iceland and the Polar Regions. This led to a slow moving cold front which lay over Northern Ireland, northern England for most of 7<sup>th</sup> January resulting in near persistent rainfall, at times extremely heavy (Environment Agency, 2006). This was followed by a deep low pressure system which moved from the west of Ireland up to southern Scotland on the morning of 8<sup>th</sup> January bringing further rainfall to Cumbria as well as high winds (Environment Agency, 2006). The weather systems can be seen in the synoptic charts in figure 2.4. Overall, 175 mm of rain fell over the Eden catchment in a 36 hour period (Day, 2005b; Fewtrell et al., 2011b) and the average exceedence probability for rainfall across Cumbria was estimated to be 0.025 (return period of 40 years) (Environment Agency, 2006).

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Figure 2.4. Synoptic charts of Met Office analysed mean sea level isobars and fronts from 18:00 UTC on 7 January 2005 and 06:00 UTC on 8 January 2005. From Cumbria Floods Technical Report (Environment Agency, 2006). © Royal Meteorological Society 2005, © Crown Copyright 2005.

## 2.5 Effects of the January 2005 flood in Carlisle

The storm over the North-West of England resulted in widespread flooding across the area and the Environment Agency issued flood warnings from Midday on 7<sup>th</sup>

January (Environment Agency, 2006). Across Cumbria, all the rivers responded with the Rivers Eden, Greta, Derwent, Cocker Kent and Eamont all reaching their highest recorded discharges (Environment Agency, 2006). In Carlisle extreme flows were recorded in the all three main rivers; the annual exceedence probabilities (AEPs) estimated in the Cumbria Floods Technical report were 0.0057 to 0.005 (return period of 175 to 200 years) for the River Eden at Sheepmount, 0.013 (return period of 75 years) for the River Caldew at Cummersdale and 0.01 (return period of 100 years) for the River Petteril at Harraby Green (Environment Agency, 2006).

The flooding in urban areas in Carlisle was widespread with all three rivers contributing to the inundation; the existing flood defences were insufficient to protect many areas of the town. Blockages from debris and sewer surcharging from the drainage systems also contributed to the damage (Environment Agency, 2005; Neal et al., 2009). Overall 3,500 homes were affected (approximately 1800 inundated) and there were two fatalities (Day, 2005b; Environment Agency, 2005). Prior to the flood the Environment Agency had already planned to upgrade the flood defences in Carlisle. The plans were then promoted and accelerated after the flood to protect against 0.005 AEP floods (return period of 200 years) across the city (Environment Agency, 2011a). The defences were completed in June 2010 (BBC, 2010).

## 2.6 Datasets used for hydraulic flood modelling in Carlisle

The availability of extensive datasets mentioned in section 2.2 as well as the severity of the flood has made the January 2005 event a popular case study for researchers. Published literature concerning the flood comprises at least 11 journal articles and conference papers: Chen (2007); Convery and Bailey (2008); Fewtrell et al. (2011b); Horritt et al. (2010); Leedal et al. (2010b); Liu and Pender (2013); Mason et al. (2007b); Neal et al. (2009); Neal et al. (2012); Pattison et al. (2014); Smith et al. (2013). In this section two important data sources needed to perform a 2-D hydraulic flood simulation of the event are characterised: the digital elevation model (DEM) for Carlisle and the observational data of the flood.



Figure 2.5. Aerial photo from 8 January 2005 showing the inundation of Brunton Park, the grounds of Carlisle United Football Club (from Environment Agency, 2011a). © 2005 Environment Agency.

### 2.6.1 Digital Elevation Models

In order to run a 2-D flood simulation, a 3-D representation of the river channel and floodplain (known as a digital elevation model or DEM) is needed. The horizontal resolution of the DEM is typically dictated by the computing power available and the size of the model domain. In theory, the higher the horizontal resolution, the more accurate the flood model and the longer the simulation takes to run. Distributed urban flood modelling has been shown to be sensitive to the resolution of the DEM used (Fewtrell et al., 2008; Yu and Lane, 2006a) with the urban model needing to be of high enough resolution to resolve the structural features affecting water flow (Fewtrell et al., 2008). When using the DEM for Carlisle, Neal et al (2012) compared model results from running the model at 5 m and 10 m resolutions and found only minor improvements in model performance when running at the higher resolution. For this project it was decided that a 10 m horizontal resolution was sufficient and the



resulting shorter simulation times would allow more runs overall of the Monte Carlo simulations described in chapter 7. Figure 2.6 shows the Carlisle DEM at (a) 10 m and (b) 1 m resolution to allow comparison of how buildings and other artefacts are represented between the two resolutions.

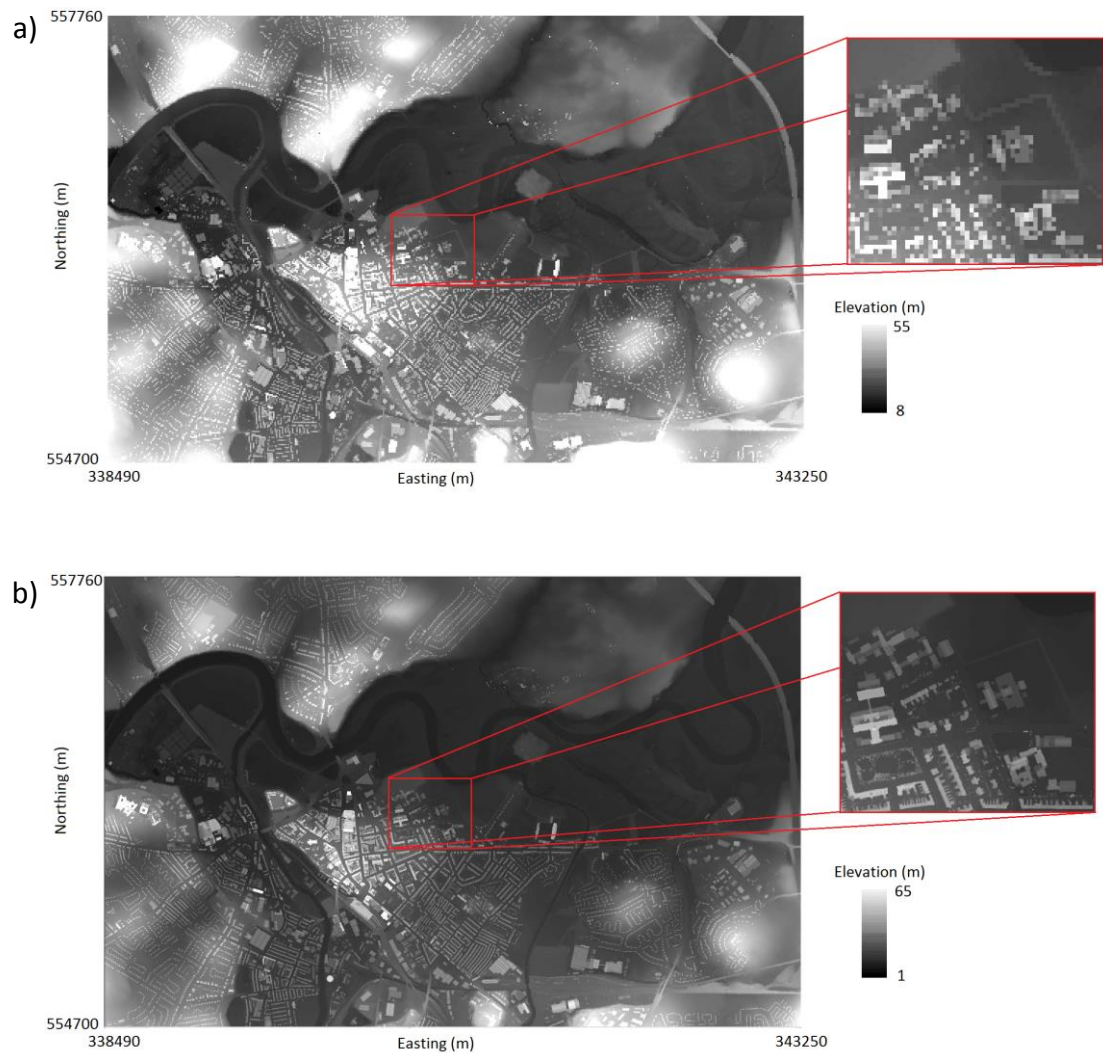


Figure 2.6. Digital elevation models of Carlisle at a) 10 m resolution (a) and 1 m resolution (b). Detail of an urban area is shown to compare building representation

Perhaps of more importance than the horizontal resolution is the vertical accuracy of the DEM. Minimising errors and inaccuracies in the ground and defence heights of the DEM is widely considered to be of paramount importance to the modelling results (interview, Senior Director, flood modelling company). The DEM was generated from two aerial LiDAR surveys performed by the Environment Agency in 2002 and 2005 (Neal et al., 2009). Mason et al. (2007b) describes the process of removing vegetation

and buildings from the 1 m resolution digital surface model (DSM) supplied by the Environment Agency to give the 'bare earth' digital terrain model (DTM). The buildings were then added back to produce the DEM using data from Ordnance Survey Mastermap topographic layer (Ordnance Survey, 2011) which includes all buildings with a footprint greater than 8 m<sup>2</sup>, although additional manual processing was required to ensure all flood embankments were represented on the DEM at the correct height (Mason et al., 2007b). Finally, the geometry of the river channels was added to the DEM from river channel cross sections supplied by the Environment Agency at 200 m intervals for the River Eden and 50 m intervals for the Rivers Caldew and Petteril (Fewtrell et al., 2011b). After consideration of the difficulties in the post-processing described above, especially in heavily vegetated areas, Mason et al. (2007b) estimate the accuracy of the DEM to be roughly  $\pm 0.18$  m in regions of short vegetation.

Throughout this project 3 variations of the Carlisle DEM were used: the DEM containing the flood defences that were in place in January 2005 were used in the simulations described in chapter 5; the design flood simulations described in chapter 7 were run both using a DEM with the latest flood defences included and using a third DEM with all defences removed.

### 2.6.2 Observational data of the January 2005 flood

There is little useful remote sensed data available for the January 2005 flood in Carlisle. The Environment Agency took some aerial photos from a helicopter (see figure 2.5 for example), but the images were taken at an oblique angle, and the time of day the photos were taken is not available which effectively prevents their use as validation or calibration data.

As an alternative to remote sensed inundation extent data, water levels recorded by river gauge data provide useful validation data. Since the gauges operated by the Environment Agency record data every 15 minutes, they are a good data source for validating the dynamics of the flood, but they are confined to the channel so their spatial coverage is limited (Neal et al., 2009). For the flood in Carlisle, by far the most extensive source of model calibration data are the data collected by two separate survey teams soon after the floods had receded. The purpose of the surveys was to

accurately locate evidence of the maximum extent or depth of the flood water in the form of either wrack marks (debris deposited by the flood) or water marks (staining) on vertical surfaces such as building walls. The locations of the wrack and water marks were recorded using differential global positioning systems (dGPS) with an accuracy of greater than 0.01 m (Horritt et al., 2010) and the combined surveys resulted in a set of 263 point measurements of water depth and extent shown in figure 2.7. Although the dGPS instruments used to record the wrack and water mark locations were considered highly accurate, the task of accurately identifying the marks is not straightforward resulting in reduced accuracy in the observational data. Chapter 4 describes the analysis performed on the observational data. The uncertainty was quantified by comparing the height of the observations with their nearest neighbours and using the water levels recorded by the river gauges as reference points. Furthermore, a smoothing technique was developed to make observations more consistent with their neighbours. The results of the application of this technique presented in chapter 4 suggest a reduction in uncertainty of the observations as a whole, but the lack of reference data means it is not currently possible to validate the results.

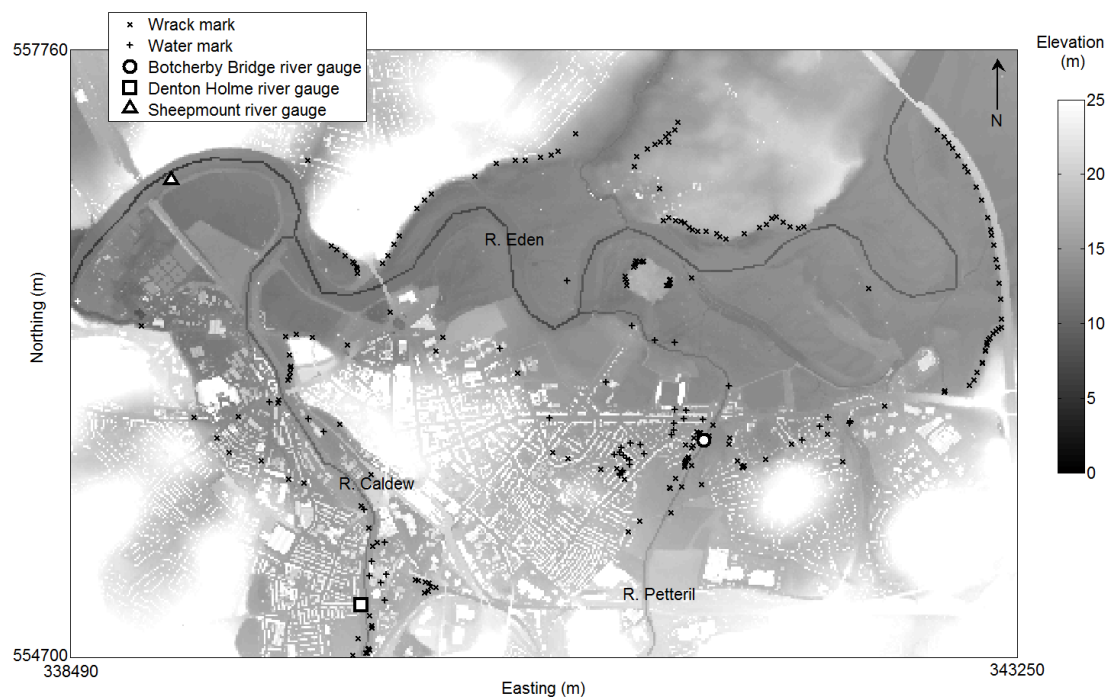


Figure 2.7. Digital elevation map of Carlisle showing the locations of the observations of wrack (x) and water (+) marks and the positions of the river gauges.

As figure 2.7 shows, the wrack and water mark measurements are not evenly distributed throughout the affected area; a large number of the wrack marks were measured in the northern and eastern shores of the Eden, not in urban areas. Of the measurements taken in urban areas, they tend to be clustered along the Caldew and Petteril, near the Botcherby Bridge gauge. Calibrating a model using these unevenly distributed points will tend to favour simulations that perform best in the areas where the density of measurements is highest. The extent of this and its possible effect on any risk-based calibration was investigated and the results presented in chapter 5.

## 2.7 Hydrometry in Carlisle

In the 1960s in Britain the management of hydrological data was passed to the Water Resources Board who implemented a great number of gauging stations, and many of these early gauges are still operated today (CEH, 2011). Currently in the UK there are over 1500 active river gauges and those located in England are operated by the Environment Agency. This project has made direct or indirect use of data from 8 gauges in and around Carlisle, the locations and details of which are shown in figure 2.9 and table 2.1 respectively. The most important source of river discharge data is the gauge located River Eden at Sheepmount. This gauge has been in operation since 1967 and records both flow and water level data every 15 minutes (CEH, 2014). The annual peak discharge data recorded by the Sheepmount gauge is shown in figure 2.8. Discharge recordings from the January 2005 flood were used in chapters 4 and 5 to provide boundary condition data for the flood models, peak flow data from the annual maximum time series was used in chapter 7 to derive the flood frequency curve for the Eden at Carlisle, and detailed discharge readings of several extreme flow events were used in chapter 8 to analyse the hydrograph shapes for the Eden.

The locations and reliability of the river gauges shown in figure 2.9 meant additional modelling and processing was required to derive the January 2005 flood hydrographs for the Rivers Eden, Caldew and Petteril flowing into the model domain (shown as the black box in Figure 2.9).



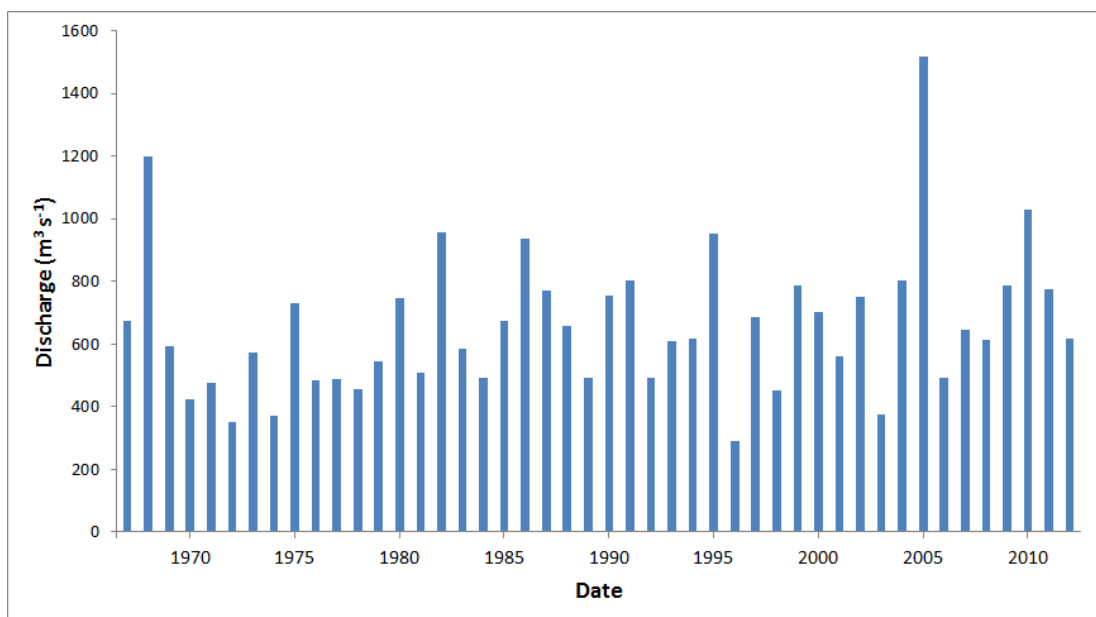


Figure 2.8. Annual Maximum (AMAX) data for the Sheepmount river gauge on the River Eden (from CEH, 2014).

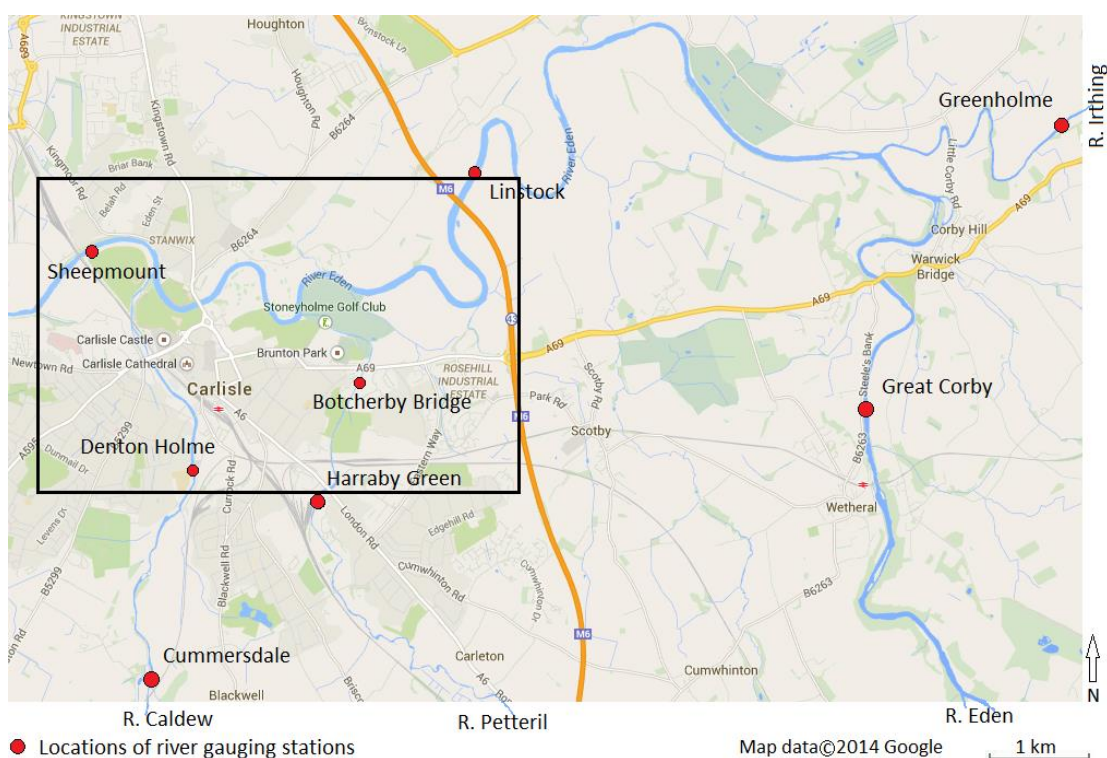


Figure 2.9. Map of Carlisle, UK and surrounding areas showing the river network and locations of the river gauges used in the study. Black box shows the extent of the hydraulic flood model. Map data © 2014 Google.

The gauge at Linstock is a level only gauge so does not provide discharge figures, furthermore a battery failure in the gauge meant data was missing between 8/1/2005 at 21:45 UTC and 10/1/2005 at 15:00 UTC (Neal et al., 2009). Neal et al (2009) describe how a linked 1D-2D model created using ISIS (2014a) and TUFLOW (Syme, 1991) was used to derive ratings for the Eden at Linstock and the Caldew where the Cummersdale gauge had been bypassed necessitating a revised rating. For the River Petteril, although the Harraby Green gauge was known to be problematic (Environment Agency, 2011f), it was estimated by Neal et al. (2009) to be within  $\pm 10\%$  when compared to simulated flows from a 2D hydrodynamic model of the area based on the Simple Finite Volume code (Horritt, 2004). The resulting hydrographs for the flood are shown in figure 2.10 where they are represented with no uncertainty; this point is addressed in chapters 5 and 7. For the purposes of the flood modelling exercises described in the chapters 4, 5 and 7 flow from the Rivers Eden, Caldew and Petteril was the only source of water into the model domain. This means the additional flow from minor watercourses, surface water flooding and backflow from drainage systems was not represented by the model (see chapter 8 for a discussion on these sources of uncertainty).

Table 2.1. River gauging stations used this project. Sources: CEH (2014); Environment Agency (2010d); Environment Agency (2011c)

Gauge	River	Level	Flow	Start	Use
<b>Botcherby Bridge</b>	Petteril	Yes	No	Oct 2001	Assessment of observations of peak flood extent (ch. 4)
<b>Cummersdale</b>	Caldew	Yes	Yes	Sept 1997	Spatial dependence (ch.8) Hydrograph shapes (ch. 8)
<b>Denton Holme</b>	Caldew	Yes	No	Jan 1999	Assessment of observations of peak flood extent (ch. 4)
<b>Great Corby</b>	Eden	Yes	Yes	Dec 1996	Spatial dependence (ch. 8)
<b>Greenholme</b>	Irthing	Yes	Yes	Aug 1967	Spatial dependence (ch. 8)
<b>Harraby Green</b>	Petteril	Yes	Yes	Dec 1969	Hydraulic model input (ch. 5) Spatial dependence (ch. 8) Hydrograph shapes (ch. 8)
<b>Linstock</b>	Eden	Yes	No	Jan 1998	Spatial dependence (ch. 8)
<b>Sheepmount</b>	Eden	Yes	Yes	Feb 1967	Hydraulic model input (ch. 5) Flood frequency estimation (ch.7) Spatial dependence (ch. 8) Hydrograph shapes (ch. 8)

## 2.8 History of flooding in Carlisle

Although the January 2005 flood is believed to be the worst flood to affect Carlisle in over 200 years (Environment Agency, 2006), it is by no means the only destructive flood recorded. In addition to the systematic time series of discharge recordings provided by the gauges listed above, records of floods can be found from searches of archive material such as local newspaper reports, a survey of flood marks made on the Eden bridge and Carlisle City Council's record of flood levels at the Eden Bridge (Environment Agency, 2006). Smith and Tobin (1979) collated records of historical floods in Carlisle to produce a list of notable events covering the period 1800 to 1970. Smith and Tobin's list was combined with other historical sources to give an updated collection of historical floods in the technical report produced by the Environment Agency subsequent to the January 2005 flood (Environment Agency, 2006). Table 2.2 summarises the floods that have affected Carlisle since 1800 combining data from historical sources with the systematic data from the river gauge at Sheepmount, more detail can be found in chapter 7.

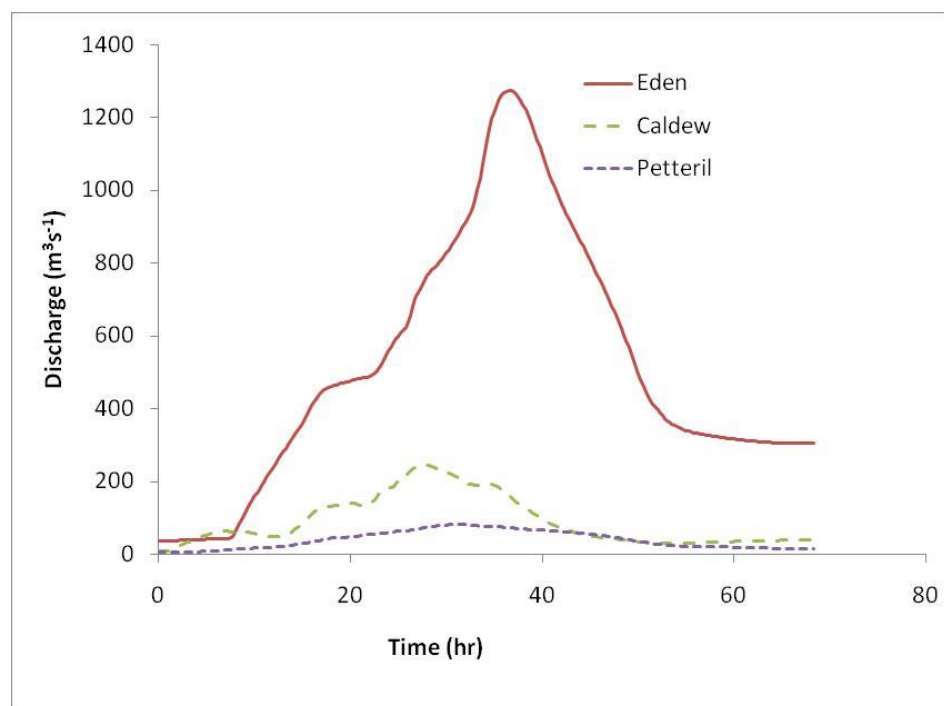


Figure 2.10. Hydrographs for the Rivers Eden, Caldew and Petteril into the Carlisle flood model domain for the January 2005 flood. Peak flows: River Eden  $1272 \text{ m}^3 \text{s}^{-1}$ ; River Caldew  $246.5 \text{ m}^3 \text{s}^{-1}$ ; and River Petteril  $82.6 \text{ m}^3 \text{s}^{-1}$ .

Start time is 00:45 UTC on 7 January 2005.

Table 2.2. Extreme historical and gauged flood data for Carlisle since 1800. Sources: Cumbria Floods Technical Report (Environment Agency, 2006) ; Smith and Tobin (1979); Environment Agency Sheepmount Gauging Station records (CEH, 2014); Carlisle Encyclopaedia references from local newspapers (Carlisle History, 2014). For historical records, the water level at the Sheepmount gauging station is calculated as approximately 1.1 m lower than the estimated level at the Eden Bridge.

Date	Estimated level at Eden Bridge (m AOD)	Estimated level at Sheepmount gauging station (m AOD)
<b>2/1809</b>	13.6 – 14.0	12.7
<b>9/1809</b>	13.6	12.5
<b>11/1815</b>	13.6	12.5
<b>2/2/1822</b>	14.00	12.9
<b>1/1/1851</b>	13.41	12.3
<b>10/2/1852</b>	13.53	12.5
<b>13/12/1852</b>	13.83	12.7
<b>8/12/1856</b>	14.19	13.1
<b>11/1857</b>	13.45	12.4
<b>11/1857</b>	13.55	12.5
<b>1/2/1868</b>	13.60	12.5
<b>7/10/1874</b>	13.83	12.7
<b>1891</b>	13.42	12.3
<b>1899</b>	13.6	12.5
<b>27/1/1903</b>	13.50	12.4
<b>2/1/1916</b>	13.37	12.3
<b>27/12/1924</b>	13.63	12.5
<b>30/12/1924</b>	13.78	12.7
<b>2/1/1925</b>	14.11	13.0
<b>21/8/1928</b>	13.45	12.35
<b>29/12/1929</b>	13.50	12.4
<b>4/11/1931</b>	14.08	13.0
<b>18/10/1954</b>	13.56	12.8
<b>9/12/1964</b>	13.40	12.3
<b>17/10/1967</b>		12.28
<b>23/3/1968</b>		13.16
<b>4/1/1982</b>		12.50
<b>21/12/1985</b>		12.43
<b>1/2/1995</b>		12.49
<b>8/1/2005</b>		14.15
<b>20/11/2009</b>		12.74

## 2.9 Channel and floodplain changes in Carlisle

Changes in land-use in the catchment, channel geomorphology and floodplain storage are all thought to affect the risk and extent of extreme floods (Jalbert et al., 2011; Pattison and Lane, 2012; Shaw et al., 2010). For the case of the rivers in Carlisle, catchment land-use changes were thought to have an insignificant effect on floods (see for example O'Connell et al., 2007), but some attempt was made to estimate the effects of channel and flood plain changes since the start of the historic period to the present day.

### **Channel changes**

A review of some of the historic maps of the area reveals that prior to the early nineteenth century the River Eden was split into two branches upstream of the location of the castle, the two branches spanned by two wooden bridges roughly in the location of the current Eden Bridge. A map from 1821 shows that the southern branch of the Eden has been filled in and the two wooden bridges replaced by a new stone one. Although this stone bridge, completed in 1815 still exists, it was widened in the 1930s (Eden Bridge, 1932). Furthermore, when the stone bridge was originally built a second span of arches was built over the location of the previous southern branch of the Eden. This second span was designed as a route to channel flood water, but was filled in in 1969 (Cumberland News, 2010).

### **Changes to floodplain storage**

The first records of attempts to reduce the flood risk in Carlisle are from reports in local newspapers the *Carlisle Journal* and the *Carlisle Patriot* (Smith and Tobin, 1979). The papers contained reports stating that embankments previously constructed by the mid nineteenth century to protect the low-lying 'holmes' next to the River Eden (Whyte, 2009) had prevented the area of Rickergate being inundated by floods in 1851 and 1856 (Smith and Tobin, 1979). In the early twentieth century larger embankments were constructed just downstream of the Eden Bridge at Bitts Park and Saucerries, with further improvements in the Botcherby area in 1931 (Smith and Tobin, 1979). This reactive approach to managing flood risk was not accompanied by a strategy to deter development in areas of high flood risk, and it was only the damaging flood of 1968

that spurred effective action from the authorities (Whyte, 2009). At the time, the 1968 flood was thought to be a 0.01 AEP (1-in-100 year) flood, and the existing flood banks were extended and strengthened to provide protection 30 cm above the 1968 flood level. However, subsequent evaluations of the return period suggest the 1968 flood was only a 0.0133 AEP (1-in-75) year event (Atkins, 2011). Certainly, the defences were insufficient in January 2005 when the flood waters rose approximately 1 m higher than any previously recorded event. The Environment Agency had already planned significant improvements to the Carlisle defences, but the anger expressed by local residents and businesses was influential in accelerating and extending the development (Environment Agency, 2009b). The £38m scheme was completed in June 2010 (Atkins, 2011; BBC, 2010) with the Eden, Caldew and Petteril protected by a series of flood banks and walls designed to withstand a 0.005 AEP (1-in-200 year) flood (Environment Agency, 2009b). In November 2009 heavy rainfall across the Lake District in the north of England caused a severe flood event in the town of Cockermouth (BBC, 2009). At that time the river Eden did exceed bank-full at Carlisle, but it seems the defences held firm and the town was not flooded (BBC, 2009). More recently, torrential rain in the summer of 2012 resulted in the highest recorded discharge on the Caldew in Carlisle, but the defences were enough to save the homes in the Denton Holme which had previously been flooded in 2005 (News and Star, 2012).

Section 7.3.1 provides more details of these channel and floodplain changes along with a description of how they are accounted for in the Bayes model used to derive the flood frequency curve for the Eden at Carlisle.

## 2.10 Hydraulic flood modelling in Carlisle

The software used in this project for simulating floods in Carlisle is LISFLOOD-FP, a raster based inundation model designed to take advantage of high grid resolution DEMs (Bates and De Roo, 2000) such as the DEM of Carlisle described in section 3.6.1. The background and design of LISFLOOD-FP is summarised in the chapter 3, this section gives details of the model configuration, implementation and execution. Table 2.3 summarises the parameters required to run and LISFLOOD-FP simulation and the values applied for this project.

### 2.10.1 Model evaluation

Once a simulation completed, the *.max* file contained a record of the maximum water level reached throughout the flood simulation for each cell in the model domain. Evaluating the performance of the simulation was then a matter of comparing the simulated maximum water levels in the *.max* file with the observations of maximum water level or extent in the observational dataset. For each observation of maximum inundation the difference between the height of the observation and the maximum simulated water level for the corresponding cell in the *.max* cell was recorded. If the maximum water level for the cell was zero (i.e. the cell remained dry throughout the simulation) then the simulated water level was taken from the nearest cell inundated by the simulation. The differences in observed and simulated water levels were analysed in a number of ways:

- Individually or in groups to assess the specific areas of the simulation, for example see section 4.4.4.
- By category of observation. For example to compare model performance in urban areas against rural areas as part of a risk-based subjective model validation. See section 5. 7
- Globally to get a single overall score of model performance. Calculating the average of all the differences between observed and simulated water heights gave an indication of any bias toward over- or under-estimating inundation by the simulation. Calculating the root mean square error (RMSE) gave a single score of how well the simulated flood extents matched the observations. Used in chapters 4, 5 and 7.

### 2.10.2 Uncertainty in hydraulic flood modelling

The GLUE methodology of Beven and Binley (1992) was used in chapters 5 and 8 to capture the uncertainty in the flood models. Specifically, the GLUE implementation in these chapters followed Aronica et al.'s (2002) method of weighting the behavioural model parameter sets based on their evaluation against the observational data, then combining the results into a 2-D probabilistic flood map.

Table 2.3 Summary of parameters and runtime command line options used by LISFLOOD-FP simulations in this project. Further details including an exhaustive list of all parameters and options can be found in the LISFLOOD-FP user manual (Bates et al., 2008).

Parameter /option	Purpose	Notes
<b>DEMfile</b>	Representation of floodplain	LISFLOOD-FP uses an ASCII raster file representation of the DEM. This DEM file provides British National Grid (BNG) coordinates (Ordnance Survey, 2007) of the model domain (338490, 554700), the cell size (10 m), number of rows (306) and columns (476) as well as the elevation of each cell in m AOD (Ordnance Survey, 2015).
<b>riverfile</b>	Representation of channels	BNG coordinates of river channels for the Rivers Eden, Caldew and Petteril were supplied in the river file.
<b>bdyfile</b>	Discharge into domain	File containing the discharge in $\text{m}^3\text{s}^{-1}$ for the Rivers Eden Caldew and Petteril at each time-step of the simulation. Time-steps in this case were every 900 seconds (15 minutes).
<b>bcifile</b>	Boundary condition file	Configures how flow is allowed to leave the domain. In this case, water could leave the domain on the western edge as a free surface flow downstream of the location of the Sheepmount river gauge.
<b>simtime</b>	Length (seconds) of event	Length, in real time, of the flood event being simulated. For the January 2005 event in Carlisle the <i>simtime</i> was 21600 seconds which is equivalent to 60 hours.
<b>nch</b>	Channel friction	Manning's <i>n</i> (Manning, 1891) value for channel friction. A uniform value was used throughout the channels. Alternatively channel segments could be given individual <i>nch</i> values by specifying them in the <i>riverfile</i> (Bates et al., 2008).
<b>nfp</b>	Floodplain friction	Manning's <i>n</i> value for floodplain friction. A uniform value was used across the domain. Alternatively, floodplain friction values for each domain cell could be supplied in a separate raster file (Bates et al., 2008).
<b>resroot</b>	Output file name root string	A string used as the root for all output and result files generated by LISFLOOD-FP. The most important output file was the .max file: a raster file of the model domain containing the maximum simulated water depth for each cell. If <i>resroot</i> is given the value 'CarlisleSim1' then the .max file will be called <i>CarlisleSim1.max</i> .



Monte Carlo simulations were prepared using uniform Latin Hypercube Sampling (LHS) (Saltelli et al., 2000) to generate 999 parameter sets to sample all areas in the model parameter space (Beven, 2008 p.56). In chapter 5 as well as varying the channel and floodplain roughness parameters across the LHS, the hydrographs for the Rivers Eden, Caldew and Petteril were modified to capture the uncertainty in the discharge readings referred to in section 2.7. In chapter 8, only the roughness parameters were varied because the uncertainty in the discharge was captured by the flood frequency analysis performed in chapter 7.

### 2.10.3 Executing Monte Carlo simulations of flood events

The execution time for running a Carlisle flood simulation on a standard desktop computer at 10 m horizontal resolution varied between 20 minutes and 2 hours depending on the specification of the computer and the complexity of the simulation (in short, more flooding = greater complexity). Running all the 999 simulations of the Monte Carlo simulation of the January 2005 event on a single, desktop computer would prove difficult enough, but the design flood simulations described in chapter 8 required over 20,000 simulations to be run. This was only feasible by using the Condor parallel computing environment in the geography department at the University of Bristol (2014). This allowed multiple simulations to be submitted as a batch to be run simultaneously using idle desktop computers on the university department's network. Typically several hundred simulations could be completed in a 24 hour period.

## 2.11 Simulating design floods

### **Estimating flood frequency curves for the River Eden**

Once the model of the January 2005 flood has been calibrated against the observational data and a set of behavioural parameter sets identified with appropriate weighting, the next stage is to identify the peak discharge of the 0.01 AEP (100 year return period) and 0.001 AEP (1,000 year return period) 'design' floods in Carlisle that are employed by policy makers and practitioners in flood risk analysis.

A Bayesian model was developed making use of both the 46 year annual maxima (AMAX) time series of peak flows recorded by the Sheepmount river gauge on the Eden and the estimates of historical flood events listed in table 2.2, this provided an

estimation of the flood frequency curve for Carlisle. The model, described in detail in chapter 7, incorporates the uncertainty due to the limited flood peak data, the inaccuracies in the gauge readings and the considerably larger inaccuracies in the historical flood estimates.

### **Spatial dependence between rivers**

During the January 2005 flood all three main rivers in Carlisle registered extreme flows and contributed to the destructive inundation (Day, 2005b). Furthermore, due to backwatering effects from the Eden the extent of the flooding was likely to be greater than the sum of separate flood events on the 3 rivers. Consequently, any attempt to simulate a 0.01 AEP flood in Carlisle it is necessary to take account of the spatial correlation in flood events between the rivers.

Chapter 8 describes how this is done using existing simulated sets of 1,000 year flood events for the Rivers Caldew and Petteril. These simulated flows were created by Neal et al. (2012) who followed the method developed by Keef et al. (2013) to generate multiple sets of events likely to occur on average in a 1,000 year period. The sets of simulated events for the Rivers Caldew and Petteril were combined with equivalent event sets created using the flood frequency curve for the River Eden derived in chapter 7. This resulted in 100 sets of peak discharge figures each covering 1,000 years of flood events for Carlisle.

### **Variation in shape and timing of hydrographs**

The peak discharge during a flood event is a key aspect of the event in determining the inundation extent, but not the only aspect. The duration of the flood as shown by the width of the hydrograph and the relative timing of the three flood peaks should also be considered when simulating design floods (Neal et al., 2012).

In order to do this, the Environment Agency supplied 15 minute time series covering all available data for the Sheepmount (Eden), Cummersdale (Caldew) and Harraby Green (Petteril) river gauges. By identifying all flow peaks above a certain threshold and extracting the rising and falling limbs either side of the peak it was possible to build a database of flood hydrographs from the three rivers. Whilst the number of

hydrographs was not extensive: 46 for the Eden, 12 for the Caldew and 25 for the Petteril, it was considered enough to establish that hydrographs could be approximated to be symmetrically triangular in shape, the width of the triangle being strongly correlated between the 3 rivers. Flood peaks on the Rivers Caldew and Petteril were generally found to precede the peak on the Eden, probably due to the relative sizes of the catchments. Chapter 8 describes how simulated triangular hydrographs are provided as input discharge data for the 100 sets of 1,000 year flood simulations.

## 2.12 Consequences of flooding

By analysing the differences within the 100 sets of 1,000 year flood simulations it was possible to estimate the uncertainty in the 0.01 AEP design flood for Carlisle and the probabilistic flood maps for the 0.01 AEP flood are displayed in chapter 8. The consequences of the flood can be assessed from several overlapping points of view. This section describes the datasets used to quantify the uncertainty of the consequences of the 0.01 AEP design flood by placing the uncertainty depicted by the probabilistic flood maps in the context of what the flood may mean to the residents of the city. All of the spatial datasets used were available in an ArcGIS (Esri, 2013) compatible format. Consequently, heavy use was made of ArcGIS to extract the intersections of the simulated flood extent data with the spatial datasets.

### **CORINE land cover data**

The CORINE 2006 land cover data (EEA, 2006) was extracted for Carlisle and used to provide a single figure for the destructivity of a simulated flood. This crude measure of a flood's severity was necessary in order to explore the sensitivity of the model chain to various inputs. The CORINE land cover (CLC) data was available in 100 m by 100 m spatial resolution which was re-sampled to match the 10 m by 10 m model resolution. The land cover data consists of categorisations of land use into one of 48 different land cover categories covering urban/industrial areas, transport facilities, agricultural land, forestry, wetlands and water bodies. For the purposes of this project only the following CLC categories were of interest:

- 111: Continuous urban fabric
- 112: Discontinuous urban fabric

- 121: Industrial or commercial units
- 122: Road and rail networks and associated land

### **Risk to property (National Receptor Dataset)**

The National Receptor Dataset (NRD) from the Environment Agency provides several themed datasets useful to flood risk practitioners (Environment Agency, 2011e). In this project the property layers for Carlisle were used in chapter 8. For each building the NRD property layers contain address data, floor area, building type and BNG coordinates, as well as a vector layer of the outline of the building. The total number of buildings at risk of inundation was estimated by resolving which buildings overlap with grid cells marked as flooded by the simulation. However, it is noted that since the finished floor levels of the building are not included, this is likely to be an over-estimate. Crucially, for the purpose of calculating the expected damage figures, each building is also designated with a code linking it to a building type in the Multi-Coloured Manual (MCM) (Penning-Rowsell et al., 2013) and a flag indicating whether or not the building has a cellar or basement.

### **Risk to population (National Population Database)**

Data covering Carlisle from the National Population Database (NPD) (Smith and Fairburn, 2008) was supplied by the Health and Safety Executive. For each building the NPD contains statistical averages for the typical occupancy of the building. Separate figures are provided for the usual occupancy during the night time, the day time during school term and the day time during school holidays. This data was used to give estimates with confidence limits to the number of people who would be directly affected by a 0.01 AEP flood.

### **Financial risk**

The data and algorithms provided with the Multi-Coloured Handbook (MCH) from the Flood Hazard Research Centre (FHRC) at Middlesex University were used to estimate the financial cost of simulated floods in Carlisle. The MCH and its more detailed companion, the Multi-Coloured Manual, (MCM) document the methods recommended by the Environment Agency for practitioners to estimate the benefits of

proposed flood protection schemes through the use of loss-probability curves (Environment Agency, 2010a; Penning-Rowsell et al., 2013; Penning-Rowsell et al., 2010). Maximum simulated water depths for inundated buildings were combined with the depth damage estimates for specific building types included in the MCH to give totals of the expected loss due to a 0.01 AEP flood. Expected losses with uncertainty were calculated for several other flood return periods and plotted to give the loss-probability curve shown in chapter 8 (figure 8.10).

## 2.13 Social research

The thesis chapters 4, 5, 7 and 8 cover the physical science research carried out for this PhD project. Chapter 9, the last core chapter, summarises the accompanying social research that was performed to add context to and explore the implications of the results of the physical science research. Most of the material in chapter 9 is taken from 19 interviews with a range of professionals involved in flood risk management. The interviews were mostly face-to-face, either one-to-one or in small groups, with representatives from the following sources:

- The Environment Agency
- Department of Environment, Food and Rural Affairs (Defra)
- City councils
- (Re)insurance companies
- The Association of British Insurers
- Academic research
- Engineering companies
- Risk management companies
- Flood risk modelling companies
- Members of the public affected by flooding

The interviews were semi-structured; the interviewer would start by giving a presentation summarising the PhD research after which the interview would cover a list of discussion points designed to cover the aspects of flood risk uncertainty that are pertinent to the interviewee.

## Part 1. FLOOD MODELLING

## Chapter 3. Review of flood modelling and uncertainty

### 3.1 Introduction

The theme of uncertainty in flood risk explored in the core chapters of this thesis is based around an interlinked chain of environmental models. To provide statistical estimates of the likelihood and consequences of flooding in an area such as Carlisle, several models need to be built, calibrated and linked together to form the modelling chain. This chapter gives background on the uncertain business of environmental modelling in general and reviews some of the established methods and processes used when building hydraulic flood models. As well as providing background and context, it is hoped this chapter will explain and justify the choices made behind the modelling techniques used in chapters 4 and 5 of this thesis. Those chapters are not without their own, shorter review sections, so this chapter provides a broader background covering a wide range of subjects. For those readers already familiar with these subjects this may be familiar territory that can be skipped.

The chapter starts with a short review of the overall subject of environmental modelling (section 3.2) followed by more detail on the evolution, contents and data requirements of hydraulic flood models (section 3.3). Section 3.4 is a discussion covering the various sources of observational data of flood extent used to calibrate and validate flood models. Section 3.5 discusses some of the ways of managing the uncertainty in the results from flood models which is linked to the methods used to evaluate the performance of a model (section 3.6) and its sensitivity to model inputs (section 3.7). Finally, section 3.8 covers the specific subject of defining risk based calibration schemes to maximise the utility of the model as a tool for quantifying the consequences of floods.

### 3.2 Environmental modelling

The purpose of environmental modelling is to provide a simplified representation of an environmental process to help us understand that process and make predictions about its behaviour. The necessity for the model to be a simplification is based on the

level of complexity of our environment. Attempts made at making precise, overly detailed predictions of the behaviour of environmental process inevitably fail due to the often chaotic nature of the systems driving natural processes. However it seems there is a reluctance to accept the premise that “all models are wrong, but some are useful” (Box and Draper, 1987) because of the apparent philosophical contradiction with science being “an attempt to work towards a single correct description of reality” (Beven, 2006).

Before the widespread use of computers in scientific research, a model would often be a physical construction, i.e. a scaled down version of reality. Indeed hardware-based physical models are still in use where the mathematics is too complex to run on a computer, examples include wind tunnels and channel flumes (Wainwright and Mulligan, 2004). However in the fields relevant to this thesis (hydrological modelling, hydraulic flood modelling and statistical modelling of flood frequencies), hardware-based physical modelling is a thing of the past.

The model structure of a computer-based environmental model typically consists of one or more computer programs that have been developed by scientists to simulate the natural process. The models tend to be categorised as: empirical (the simplest way of describing the observed behaviour); conceptual (where the model is made up of components supposed to represent the distinct processes being represented, but the components are typically still empirical models); and physically based (derived from established physical principles and produce results consistent with the observations) (Wainwright and Mulligan, 2004). In reality, most non-trivial models are a mixture of these types. Model parameters are settings that can be changed at time of model execution in order to give the model greater generality, for example the HBV lumped rainfall runoff model has 16 parameters covering such things as the maximum soil moisture storage and the recession coefficient to runoff (Siebert, 2005). The final, vital component needed to run the model is the input data. This generally consists of observations of environmental measurements or outputs from other models (Edwards, 2010), such as time series of temperature readings, initial conditions of soil moisture or geographical representations of the study area.



### 3.2.1 Model calibration

For a parameterised model that doesn't fall into the category of being purely physically based, it is generally not possible to provide optimal values for the model parameters based purely on the knowledge of the system being modelled, an extreme example being the case where the parameters represent historical data that no longer exists (Wainwright and Mulligan, 2004). If this is the case the model parameters will need to be 'tuned' against a set of observations in order to identify the settings that result in the best fit between model output and the available observational data (Janssen and Heuberger, 1995). If the model is simple, quick to execute, with only a few parameters, then the calibration process may not require a great deal of thought and the modeller can be confident of finding an optimal parameter set using a basic sampling strategy for the parameters. However, as the number of coordinates in the parameter space increases exponentially with the number of model parameters and variables, so attempts to identify an optimal model configuration based on a strategy of attempting to sample every single point in the parameter space quickly becomes unfeasible. Often the first step in defining an overall sampling strategy is to perform a sensitivity analysis (section 3.7) to identify which parameters the output of the model is most sensitive to and which could safely be ignored, or possibly even removed from the model altogether.

### 3.2.2 Model validation

The distinction between model calibration and validation is a fine one, and the word *validation* itself is sometimes considered inappropriate because it implies that the model is in some way a *true* representation of reality rather than an approximation (Beven, 2008; Shaw et al., 2010). Oreskes et al. (1994) suggest *bench-marking* as a more appropriate term. Fishman and Kiviat (1968) define the process of validation as testing "whether a simulation model reasonably approximates a real system". For a model that has already been calibrated, the validation process needs to be carried out using a different set of observations than were used for calibration. The validation data could be from different locations, scales or output variables (see for example Andersen et al., 2001; Moussa et al., 2007; Refsgaard, 1997; Rykiel, 1996; Shih and Yeh, 2011). The validated model can then be considered as an acceptable approximation of a

broader set of scenarios/conditions than a model calibrated against a single set of observations which may suffer from 'overfitting' (Beven, 2006; Lee et al., 2012). The problem facing modellers concerned with extreme flood events is that the data is, by definition, rare, so it is often infeasible or impossible to carry out effective model validation.

### 3.2.3 Uncertainty in environmental modelling

The uncertainty inherent in the environmental model does not only apply to the model structure; the input data, parameters, boundary conditions and the observed data used to calibrate the model or validate the results are also incomplete approximations of reality (Beven, 2008). Furthermore, simple environmental models tend to have a large number of degrees of freedom, and for distributed models where each individual pixel can be characterised by several continuously varying parameters (Aronica et al., 2002), the degrees of freedom become effectively infinite. In these circumstances it is widely recognised that many combinations of input data, model parameterisation and structure may fit the (often sparse) validation data equally well; a concept known as equifinality (Beven, 2006). Whilst the principle of equifinality may be accepted in principle, there remains a strong urge to search for a single optimal representation of reality, even when the model components are known to be wrong (Beven and Freer, 2001). This approach of attempting to identify a single, optimal configuration can be particularly problematic for distributed models if a single, global value is used for a parameter that may vary spatially and temporally by significantly (sometimes by an order of magnitude) over the model domain (Beven, 2008).

### 3.2.4 Sources of uncertainty: epistemic versus aleatory uncertainty

The many and varied sources of uncertainty pertinent to environmental models can roughly be categorised either as epistemic uncertainties which arise from an imperfect knowledge of the system being modelled and aleatory (also known as stochastic) uncertainties which can be thought of as truly random (Beven, 2008). Examples of epistemic uncertainties include imperfect knowledge of precipitation and temperature data or a simplification of terrain using a digital elevation model whereas aleatory uncertainty can be found in areas such as turbulent flow or the chaotic nature of weather systems that inhibits accurate long term weather forecasts. The progression

of environmental modelling therefore is in minimising epistemic uncertainty by providing ever more realistic representations of the natural processes whilst accurately characterising the aleatory uncertainties probabilistically (Merz and Thielen, 2009). These ideals are followed in the chapters that follow; chapters 4 and 5 are primarily concerned with minimising and quantifying some of the epistemic uncertainties inherent when modelling a hydraulic model of a flood event and chapters 7 and 8 are dedicated to representing the aleatory uncertainties affecting flood frequency analysis, hydrograph variability and spatial dependence between river flows.

### 3.3 Flood models

The development of flood modelling has been largely dictated by the limitations of the computing power available to the modeller and the accuracy of the topographical data and boundary conditions of the scenarios being modelled.

In the nineteenth century the work of Claude Louis Navier, George Gabriel Stokes and Adhémar Jean Claude Barré de Saint-Venant on fluid dynamics gave rise to the Navier-Stokes equations describing the motion in three dimensions of fluid substances and the Saint Venant Equations of shallow water flow (Barré de Saint-Venant, 1871). Solutions to these equations underpin many of the various flood models in current use. Often the partial differential equations cannot be solved explicitly so numerical approximation methods need to be applied which require increasingly powerful computers as the models become more complex and work at a higher resolution. Early models used 1-D approximations for channel flow, with a succession of model designs applying differing approaches: 1-D+ (1-D plus a storage cell simulation of floodplain flow); 2-D (solution of the 2-D shallow water equations); 3-D (solution of the Reynolds averaged Navier-Stokes equations) (Pender and Néelz, 2010).

#### 3.3.1 One-dimensional (1-D) flow modelling

1-D models remain very effective at simulating the river flow through a range of hydraulic structures such as weirs and sluices; the ISIS river modelling system was first developed in 1975 and has evolved to handle complex channel networks and structures (Evans et al., 2004).

The St Venant equations for describing the flow of incompressible fluids in a channel are in predominant use as the basis for 1-D flow modelling. The equations can be expressed as two partial differential equations as follows:

- Continuity or mass conservation equation

$$\frac{\partial Q}{\partial x} + \frac{\partial A}{\partial t} = 0 \quad (3.1)$$

- Momentum conservation equation

$$\frac{1}{A} \frac{\partial Q}{\partial t} + \frac{1}{A} \frac{\partial}{\partial x} \left( \frac{Q^2}{A} \right) + g \frac{\partial h}{\partial x} - g(S_0 - S_f) = 0 \quad (3.2)$$

Where  $Q$  is the stream discharge,  $A$  is the cross-sectional area of the channel,  $g$  is the acceleration due to gravity,  $h$  is the cross-sectional averaged depth,  $x$  is the distance,  $t$  is the time,  $S_0$  is the bed slope downstream and  $S_f$  is the friction slope. The St Venant equations can only be solved analytically for very simple cases limiting their use until the availability of cheap computing power permitted the use of several classes of numerical methods in models to calculate approximate solutions for the shallow water equations (see Pender and Néelz, 2010 for a summary). It is acceptable in many scenarios to apply simplifications by neglecting some of the terms in the momentum conservation equations. For example, the LISFLOOD-FP model used in this project simulates the passage of the flood wave along the channel reach by solving the kinematic wave approximation to the momentum conservation equation (equation 3.2) (Bates and De Roo, 2000). This is achieved by neglecting the first 3 terms in equation 3.2 (local acceleration, convective acceleration and pressure) to leave:

$$-g(S_0 - S_f) = 0 \quad (3.3)$$

Rearranged to give the kinematic wave equation:

$$S_f = S_0 \quad (3.4)$$

Thus in the LISFLOOD-FP model implementation the friction slope ( $S_f$ ) is approximated to water surface slope ( $S_0$ ) (Bates and De Roo, 2000). This means, if it can further be assumed that the rate of head loss due to friction is approximately the same as that under steady, uniform flow, one of the uniform flow formulae can be

used to derive the friction slope (Shaw et al., 2010 p. 371). Whilst there are several alternative uniform flow formulae (Darcy-Weisbach equation, Chézy equation), Manning's equation is most commonly applied in the UK (Pender and Néelz, 2010), and this is the equation used by the LISFLOOD-FP model, both for the 1-D flow within the channel and to dictate the flow-rate between cells in the floodplain (Bates and De Roo, 2000). Manning's equation is often implemented in the form (Shaw et al., 2010):

$$S_f = v^2 n^2 R_h^{-4/3} \quad (3.5)$$

Where  $R_h$  is the hydraulic mean radius ( $R_h = A/P$ , where  $P$  is the wetted perimeter and  $A$  is the cross sectional area),  $n$  is the Manning friction coefficient and  $v$  is the mean velocity, from  $v = Q/A$ . The LISFLOOD-FP model uses a rectangular channel, so a common approach to simulate a real channel is to match the cross sectional area of the rectangular channel to the real channel cross section at bank-full (Neal et al., 2009).

### 3.3.2 Two-dimensional (2-D) flow modelling

Once the water exceeds bank-full depth and water starts flowing onto the floodplain, it can no longer be described in terms of 1-D flow; the water must be allowed to flow in two dimensions with the depth also varying across the inundated area. The 2-D versions of the St Venant equations are known as the shallow water equations. There are now three unknowns: depth and the velocity components in two horizontal directions, consequently three equations are required:

- Continuity or mass conservation equation:

$$\frac{\partial h}{\partial t} + \frac{\partial hu}{\partial x} + \frac{\partial hv}{\partial y} = 0 \quad (3.6)$$

- Momentum conservation equations in 2 dimensions:

$$\frac{\partial hu}{\partial t} + \frac{\partial (gh^2/2 + hu^2)}{\partial x} + \frac{\partial huv}{\partial y} = gh(S_{0x} - S_{fx}) \quad (3.7)$$

$$\frac{\partial hv}{\partial t} + \frac{\partial huv}{\partial x} + \frac{\partial (gh^2/2 + hv^2)}{\partial y} = gh(S_{0y} - S_{fy}) \quad (3.8)$$

Where  $x$  and  $y$  are the two horizontal spatial dimensions,  $u$  and  $v$  are the depth averaged velocities in the  $x$  and  $y$  directions respectively, and  $S_{0x}$  and  $S_{0y}$  are the ground slopes in the  $x$  and  $y$  directions. Some inundation models can claim to be fully 2-D by solving simplified shallow water equations on the floodplain; for example ESTRY-TUFLOW (Syme, 1991), SFV (Horritt, 2004) and TELEMAC-2D (Galland et al., 1991; Hervouet and Van Haren, 1996). Other model codes such as JFLOW (Bradbrook, 2006) and LISFLOOD-FP (Bates and De Roo, 2000) use a simpler approach to calculating floodplain flow. The floodplain is divided into a regular grid with each cell treated as a storage volume for which the continuity equation needs to be solved. The flow rates between each cell are calculated using the Manning equation (equation 3.5), such that the flow rate between two adjacent cells  $i$  and  $j$  is:

$$Q_{ij} = \frac{A_{ij} S_{ij}^{1/2} R_{ij}^{2/3}}{n} \quad (3.9)$$

Where  $Q_{ij}$  is the flow between the cells,  $A_{ij}$  is the cross-sectional area between the two cells,  $R_{ij}$  is the hydraulic radius,  $S_{ij}$  is the water surface slope between the two cells and  $n$  is the Manning friction coefficient. One of the driving factors behind the development of LISFLOOD-FP is to provide a physically-based model that can take advantage of high-resolution floodplain elevation models, whilst implementing the simplest possible process capable of describing 2-D dynamic flood inundation (Bates and De Roo, 2000). Bates and De Roo (2000) argue that the two dimensional diffusion wave representation of floodplain flow is sufficient to achieve acceptable predictions when compared to typically available flood extent data. They note that variables such as flow velocity are not generally collected by environmental authorities nor are they required by statutory flood risk authorities, therefore they can be ignored by the model. The advantages of this approach are that the model is simple to set up, computationally efficient and easy to integrate with third party GIS systems (Bates and De Roo, 2000). The main disadvantages, however, is that LISFLOOD-FP models are more sensitive to parameters than more complex models such as TELEMAC 2D which explicitly represents more of the energy loss mechanisms (Di Baldassarre et al., 2010). Consequently the Manning's friction parameters used by LISFLOOD-FP must act as 'effective' parameters to compensate for the fact that the model is not fully physically

realistic. This means LISFLOOD-FP simulations are unable to make accurate predictions of inundation extent unless calibrated against previous inundation area data (Horritt and Bates, 2002).

There have been several alterations to Bates and De Roo's (2000) original LISFLOOD-FP code. Hunter et al. (2005b) introduced an adaptive time-step (ATS) scheme to analytical solutions of wave propagation that is independent of initial time step. However, the time step within the ATS version of LISFLOOD-FP is still proportional to the square of the grid cell size resulting in computational intractability for models with high resolutions (Neal et al., 2011). Bates et al. (2010) formulated a LISFLOOD-FP version that uses simplified 1-D shallow water equations with minimised physical representation that allows a time step that is directly proportional to the grid cell size (Neal et al., 2011). Thus the performance of the simulations scales more favourably as the model resolution increases allowing sub-10m simulations required for urban flood modelling (Fewtrell et al., 2008). It is Bates et al.'s (2010) version of LISFLOOD-FP that is used for the flood simulations performed for this project unless otherwise stated.

### **Urban flood modelling**

Modelling floods in urban areas brings a unique set of challenges for the modeller. The scale of the buildings and other structures of varying scales (Mignot et al., 2006) affecting water flow and floodplain volume need to be adequately represented by the digital elevation model (DEM) (Yu and Lane, 2006a) sometimes necessitating horizontal grid scales of less than 10 m (Bates, 2012). The blockage effects by any structures not correctly represented in the DEM plus the widely varying friction coefficients typical of floodplains incorporating urban areas stretch the ability to use a global floodplain friction value as an 'effective' parameter (Fewtrell et al., 2008; Mason et al., 2007b; Yu and Lane, 2006b). It may also be necessary to model the effects of urban drainage systems (Hsu et al., 2000; Mark et al., 2004; Schmitt et al., 2004).

#### **3.3.3 Digital Elevation Models**

As the resolution of the 2-D and 3-D models increases, so it becomes more important to provide the model with an accurate topography of the channel and

floodplain (Mason et al., 2007b). Originally topographical surveys were a labour intensive way of mapping the terrain, but the use of aerial LiDAR surveys over areas at risk of flooding mean that far more accurate 3D terrain maps can be produced (Bates et al., 2003). LiDAR maps out the land surface by bouncing a series of laser pulses from an aircraft or satellite and calculates the distance to the target from the return time of the pulse.

The Shuttle Radar Topography mission has mapped out the entire land surface to a vertical resolution of nearly  $\pm 6\text{m}$  (Farr et al., 2007), but this is not sufficient detail for the purposes of flood modelling. Surveys carried out using state of the art LiDAR systems on board rotating wing aircraft can provide a vertical resolution as low as 0.05 m (Geomatics Group, 2015). As of April 2015, the Geomatics group of the Environment Agency have mapped 70% of England and Wales with LiDAR with a vertical resolution varying from 0.05m to 0.15 m (Geomatics Group, 2015). LiDAR data can be used to derive, not just the raw earth elevation (from the last bounce returns of the pulses), but also some information of the vegetation cover above ground. The nomenclature of the elevation models produced from the LiDAR data can be confusing: the model that requires the least post-processing from the LiDAR is the *digital surface model* (DSM) which includes both vegetation and buildings. The vegetation height can be calculated by comparing the first and last bounce returns of the pulses and the vegetation removed from the model to produce a *digital elevation model* (DEM) that still contains buildings.

Many schemes have been developed to remove buildings and other artefacts from the model to give the 'bare earth' *digital terrain model* (DTM) (Mason et al., 2007b). The UK Environment Agency have developed a system that uses commercial TERRASCAN software to convert a DSM to a DTM along with a separate vegetation map (Mason et al., 2007b). Whilst LiDAR cannot detect covered gaps such as drainage channels or bridges, these can be manually added to the DEM (Smith et al., 2006). Similarly if the resolution of the DEM is not high enough to resolve flood defence crest heights accurately these may need to be added to the DEM manually (Neal et al., 2012) because they are likely to have a particularly significant effect on the flood simulation.



Table 3.1 Summary of features of DTM's, DSM's and DEM's (from Smith et al., 2006).

<b>Model</b>	<b>Features</b>
<b>Digital Surface Model (DSM)</b>	<b>A representation of a surface using 3D coordinates. Contains all above ground features ('first bounce' returns of LiDAR pulses)</b>
<b>Digital Terrain Model (DTM)</b>	<b>'Bare earth' model of Earth surface. Created by stripping off above ground features from DSM</b>
<b>Digital Elevation Model (DEM)</b>	<b>In flood modelling terms, this is the elevation model that is appropriate to the area of interest. Typically it is the DTM with layers added that are pertinent to the model. For example, buildings, bridges, culverts, flood defences.</b>

### 3.3.4 Discharge into the model domain

Once an accurate DEM of the reach has been prepared and a model that simulates the behaviour of water has been programmed, the final stage of the flood modelling process is to 'just add water'. Flood water can arrive directly from the sky, from rivers and streams, storm surges leading to coastal flooding, urban drainage systems, snow or glacier melt or groundwater level rises (Pitt, 2007). This project is concerned with flooding caused by river flow exceeding bank-full, so it is important to know the discharge into (and out of) the study area – these are known as boundary conditions.

There are approximately 1400 river gauging stations in the UK, mostly recording river levels every 15 minutes (Marsh, 2002). Technological advances such as the use of ultrasonic flow gauges have been implemented in a minority of stations which allows accurate measurements of discharge for stable river sections, but the majority of stations calculate the discharge indirectly from the stage-discharge relation using a rating curve (CEH, 2011). The accuracy of this method relies upon an up to date knowledge of the channel geometry and repeated measurements of water velocity across a range of river stages which allows the construction of the rating curve. Whereas the majority of gauging stations in the UK have been found to have an

accuracy of within 5% during normal flow periods, this is often not the case during periods of extreme flow, either high or low (Marsh, 2002). Unfortunately, for the purposes of flood modelling, the technical and logistical difficulties of defining the rating curve when the flow is above bank-full and likely to bypass the gauge means the uncertainty in the discharge figures is much greater during flood events (Marsh, 2002).

It may be necessary therefore to expend considerable effort investigating the extent and effect of the uncertainty in the boundary conditions before even attempting to simulate the flood event. Pappenberger et al. (2006a) attempt to assess the sensitivity of a model of a flood on the river Alzette (Luxembourg) to the discharge uncertainty and found it to exceed that of many model parameters, so should be considered during the calibration process. Horritt et al (2010) describe the process of re-rating river gauges subsequent to the January 2005 flood in Carlisle, UK using a hydrological model driven by data from other, more reliable nearby gauges. Domeneghetti et al. (2012a) find that rating curve errors can negatively influence the derived roughness coefficient parameters.

For the cases where there are no river gauge data to provide boundary conditions for the flood model it may be necessary to implement a hydrological model simulate the discharge based on the precipitation over the river catchment (for example Lhomme et al., 2010).

### 3.4 Observational data of flood extent

All commonly used flood models will have parameters that affect the behaviour and output of the flood simulations. As discussed in section 3.3.2, these parameters may not be “physically-based” and even those that are will almost certainly not be accurate representations of reality (Beven, 2008). Consequently, if a flood event has previously occurred in the model domain, any observational data of the flood is used to calibrate the model in the hope of identifying the parameter sets that are a useful representation of reality (Hunter et al., 2005a). Extreme flood events are, by definition, rare so any data on the spatial extent of the flood is beneficial to the model calibration process (Hunter et al., 2005a).

Remote sensed data such as aerial images from aircraft have been used to assess flood extent since the early 20<sup>th</sup> century (Bhavsar, 1984). High quality aerial photography remains the most accurate method of remote sensing flood extent, however the high cost of the airborne survey mean images from satellites are often the only feasible source of remote sensed data (Schumann et al., 2009). Recently, when Tewkesbury was flooded by the River Severn in July 2007 (Marsh and Hannaford, 2007), high resolution (3 m) images from the German Aerospace Centre's TerraSAR-X satellite (Eineder et al., 2009) were used by Mason et al. (2010) to detect the floodwater in the urban areas from the TerraSAR-X image.

Unfortunately the TerraSAR-X satellite had not been launched when Carlisle flooded in January 2005, and the poor meteorological conditions ruled out high quality aerial photography, so there is no useful remote sensed images of the flood. There is, however, good quality locally surveyed data of evidence of the maximum extent of the water as described in chapter 2. For the Carlisle flood, the observational dataset takes the form of a set of recordings of the locations either of debris deposited by the water on shallow gradients (wrack marks) or staining on vertical surfaces (water marks).

Observational datasets in this form can then be used to calibrate 2-D models, either as the primary observational data (e.g. Mignot et al., 2006) or as a supplement to other sources of inundation data (Hunter et al., 2005a; Schumann et al., 2007b). This can be a time consuming exercise, and won't provide a full record of the extent of the flooding, but it does have the advantage of being a recording of the peak or very nearly peak extent of the flood water and can be carried out up to several weeks after the flood event. Related locally sourced methods for establishing flood extent can involve interviewing and collecting photos from witnesses of the event (for example Connell et al., 1998; Parkin, 2010).

### 3.5 Uncertainty in flood modelling

The principle of equifinality, where many combinations of input data, model parameterisation and structure may fit the observed data equally well, is perhaps particularly relevant to 2-D hydraulic flood modelling. For a 'hybrid' model such as LISFLOOD-FP which represents the physical characteristics of a flood but with some

simplifications, the model calibration process often forces *effective values* on global parameters so that they can compensate for physical processes that are not represented in the model (Beven, 2008).

For example, when simulating a flood event using LISFLOOD-FP, it is possible to use a single global parameter value for the Manning's  $n$  friction coefficient on the floodplain which is expected to represent an average across the domain. However, floodplains, especially those incorporating urban areas, may contain terrain with widely varying friction coefficients (e.g. woodland vs. asphalt), and since the resolution of the model may not be high enough to account for all the structural features in the topology that will affect the flow of water, the Manning's  $n$  for the floodplain must incorporate an *effective* element to represent the physical processes (Neal et al., 2009). So selecting a single, global value for Manning's  $n$  across the domain may be unacceptable.

Even if an optimal value for a global friction coefficient could be found for a model configuration that adequately represents reality at the point in time at which the model is being calibrated, this situation may break down throughout the course of the flood event and could be an important factor when attempting to use the model set-up to represent subsequent events with different boundary conditions.

In the past two decades, as the availability of computing resources has increased, it has become easier to apply random sampling methods across the model parameter space to find the optimal parameter set (Vrugt et al., 2003). Even complex parameter surfaces with multiple local minima can be efficiently and effectively searched by automatic calibration algorithms such as the shuffled complex evolution (SCE-UA) global optimisation algorithm developed by Duan et al. (1993) or simulated annealing (Sumner et al., 1997). But more recently, as the intrinsic inaccuracy of environmental models and observations is acknowledged, so the emphasis has shifted from finding a single optimum in the parameter space to identifying the subset of acceptable model realisations (Vrugt et al., 2003). This has led to the emergence of the equifinality problem across a wide range of model classes, even for models of moderate simplicity

(Beven and Freer, 2001). Early examples of studies allowing for equifinality in flood inundation modelling include Romanowicz et al. (1998) and Aronica and Beven (1998).

There are several approaches to tackling the identification of uncertain parameter distributions. These include the use of multi-normal approximations (Kuczera and Mroczkowski, 1998), Markov Chain Monte Carlo methods (Bates and Campbell, 2001; Kuczera and Parent, 1998) and techniques based on Bayesian inverse methodology such as the Shuffled Complex Evolution Metropolis algorithm (SCEM-UA) proposed by Vrugt et al. (2003), the Bayesian Recursive Algorithm (BaRE) from Thiemann et al. (2001) and, more recently, differential evolution adaptive metropolis (DREAM) (Vrugt et al., 2009).

Methods that focus on assessing global uncertainty without attempting to separate uncertainties in input, parameter and model implementation, and observations (Feyen et al., 2007) include the meta-Gaussian approach (Krzysztofowicz and Kelly, 2000) and the generalised likelihood uncertainty estimation (GLUE) methodology first described by Beven and Binley (1992). Perhaps driven by its simplicity and ease of implementation (Vrugt et al., 2009), the GLUE methodology has been used widely in hydrological and hydraulic modelling (e.g. Aronica et al., 2002; Hunter et al., 2005a; Uhlenbrook and Sieber, 2005). But there has been lively debate, particularly in the hydrological modelling community, that GLUE can result in statistically unreliable parameter distributions because it does not use a formal or Bayesian representation of model error (see for example Beven et al., 2007a; Beven and Young, 2003; Beven et al., 2008; Gupta et al., 2003; Mantovan and Todini, 2006; Thiemann et al., 2001 and many more). It seems the debate on formality of error representation will continue.

By applying the GLUE methodology, the aim is to establish a set of model realisations that are considered behavioural and attach a likelihood to each behavioural model realisation such that the likelihood increases with model performance (Beven, 2008). In this way the errors associated with the particular model realisation are incorporated because the scale of the uncertainty is assumed to be consistent during calibration and prediction (Beven, 2008p. 164). In order to apply

GLUE methodology the following steps are performed to arrive at the subset of model realisations considered behavioural (from Beven, 2008):

- Define which model parameters are considered uncertain.
- Decide how the uncertain parameters are to be sampled.
- Define the criteria for deciding whether a model is behavioural or not.
- Define the likelihood measure for evaluating the behavioural model runs such that:
  - The likelihood is zero for those model realisations considered non-behavioural.
  - The likelihood increases as the level of model performance increases.
  - The likelihood should be scaled to sum to unity over all the models retained as behavioural.

As already mentioned, some of the criticism of GLUE stems from the ability to use subjective, informal likelihood measures rather than a formal representation of model error (Beven, 2006). As Beven (2008 p.122) points out the GLUE methodology will produce equivalent results to the Bayesian approach *if* a formal likelihood function is used rather than using an informal measure and implicit error handling. However it seems there is some scope in selecting the likelihood measure so as to suit the data and event being modelled: Beven and Freer (2001) describe several likelihood measures and their appropriateness to environmental modelling; Beven (2006) shows a simple triangular relative weighting scheme (Figure 3.1) (equivalent to a fuzzy membership function) which can be extended to take account of observation uncertainty (Figure 3.1b) or a more complex distribution (for example a Beta function) with range limits can be used (Figure 3.1c); Pappenberger et al. (2006a) use a likelihood function where parameter set acceptability is based on a two-dimensional fuzzy membership function.

The decision whether a model realisation is behavioural or not, like the choice of likelihood function, is often subjective and may depend not only on the uncertainty and distribution of the available observational data (Schumann et al., 2007b) but also the eventual goal of the modelling exercise. For example, if the modeller can identify

areas in the model domain where the consequences of flooding are greatest, then it may be appropriate to consider spatial variation in model performance (Pappenberger et al., 2007b) such that local model performance measure weighted towards areas of high vulnerability is selected over a global performance measure (Beven, 2006).

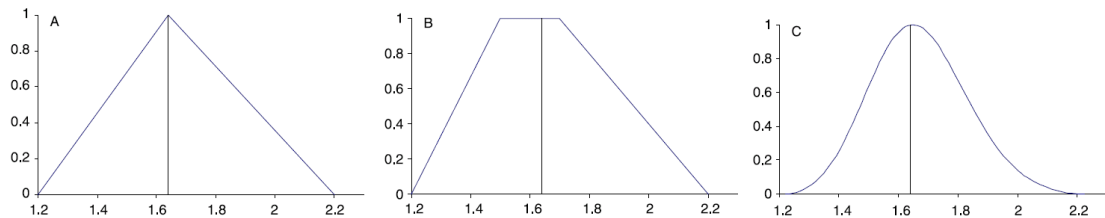


Figure 3.1. Graphical representations of examples of likelihood functions that could be applied in a GLUE methodology. The observed value (vertical line) of the model output measure is not central to the acceptable range. (A) Triangular with peak at observation; (B) Trapezoidal, with a core range of acceptability to take account of uncertainty in the observation; (C) Beta distribution with defined range limits.

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### 3.6 Evaluating model performance

It is essential to define the measure used to evaluate a model's performance prior to calibration (Schumann et al., 2009). This is an area where subjectivity can be applied to favour model realisations that perform well for the circumstances in which the researcher is particularly interested. For example, in hydrological modelling a widely used method of evaluating a time series of simulated discharge values is the Nash-Sutcliffe efficiency index (*NS*) (McCuen et al., 2006) given by (Nash and Sutcliffe, 1970),

$$NS = 1 - \frac{\sum(Q_{obs} - Q_{sim})^2}{\sum(Q_{obs} - \overline{Q_{obs}})^2} \quad (3.10)$$

Where  $Q_{obs}$  and  $Q_{sim}$  are the observed and simulated discharges respectively and  $\overline{Q_{obs}}$  is the mean observed discharge. Whilst assessing 2-D flood models by comparing observed and simulated discharge figures is a useful way of checking one aspect of the model's performance, it is generally the extent of the water on the floodplain that is of more interest to the modeller. Scoring methods for this are discussed in the next section.

### 3.6.1 Scoring models against observed water extent

Where flood extent data is available there are several approaches to comparing observed and simulated inundation and reducing the comparisons to a single model score. The first step is often to start with a visual comparison; this allows an experienced modeller to check for consistency and hydraulic feasibility (Schumann et al., 2009). However it is desirable to apply a quantitative measure for an objective assessment. Where the primary source of observational data are remotely sensed images of flood extent, a common approach is to use a discrete pixel by pixel comparison where pixels are treated either as flooded or unaffected (wet or dry) (Schumann et al., 2009). Comparable measures are proposed by Bates and De Roo (2000), Horritt and Bates (2001b), Aronica et al. (2002) and Hunter et al. (2005a) and reviewed in Schumann et al. (2009). It may be that there are remote sensed images from multiple times during the flood event. This additional information may be useful to the modeller in terms of providing information on how well the model represents the dynamics of the flood event, and an appropriate measure combining all observations can be defined.

### 3.6.2 Scoring models against point observations of maximum water surface elevation or extent

For the modelling of events where the observational data takes the form of point observations of peak water depth or extent, a global measure of model performance can be calculated by examining the simulation of maximum water depth at the location of each of the points of observation. Typically a measure of average absolute difference between observed and simulated water depth is used to give an overall summary of the skill of the model, for example the root mean square error (RMSE) shown in equation 3.11 or sum of absolute errors (SAE) shown in equation 3.12 (for examples see Hunter et al., 2005a; Mignot et al., 2006; Neal et al., 2009). The mean error (equation 3.13) may also be used to highlight any model bias towards over- or under-prediction.

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (WD_{obs_i} - WD_{sim_i})^2} \quad (3.11)$$



$$SAE = \sum_{i=1}^n |WD_{obs_i} - WD_{sim_i}| \quad (3.12)$$

$$mean\ error = \frac{1}{n} \sum_{i=1}^n WD_{obs_i} - WD_{sim_i} \quad (3.13)$$

Where  $n$  is the number of observations,  $WD_{obs}$  is the observed water depth and  $WD_{sim}$  is the simulated water depth at the location of the observation. If the simulation predicts no water at the location of the observation then either the elevation of the DEM at that location (e.g. Hunter et al., 2005a) or the water surface elevation at the location of the nearest simulated wet pixel (e.g. Neal et al., 2009) can be used for  $WD_{sim}$ .

### **Combining distinct sets of observation**

The scarcity of observational data of extreme floods available for calibrating flood models may lead to the desire to define ways of combining separate sets of observational data into a single model score. Hunter et al. (2005a) describe how data from river gauges, SAR images, an aerial photo and point observations of maximum water surface can be combined under a GLUE methodology. Going a step further, if data from multiple flood events become available, Romanovicz and Beven (2003) describe the process of updating a generalised likelihood measure of model performance to take account of the additional data.

### **3.6.3 Spatial variation in model uncertainty**

Whereas a single measure can be a useful indicator of model performance, and may play a part in categorising model realisations as behavioural, there is likely to be considerable spatial variation in the differences between observations and simulation. These variations may arise both from a spatial variation in the model's performance and uncertainty in the observational data themselves.

Aronica et al. (2002) establish a map of spatial variation in model performance by running a Monte Carlo simulation to generate a sample of all feasible model realisations as defined by the parameter selection criteria required for a GLUE procedure. They then calculate a global measure of model performance for each

realisation and combine the results from all model realisations to give a flood probability  $P_i^{flood}$  for each pixel  $i$ :

$$P_i^{flood} = \frac{\sum_j f_{ij} F_j}{\sum_j F_j} \quad (3.14)$$

Where  $F_j$  is the global performance indicator for simulation  $j$  and  $f_{ij}$  is 1 for a pixel predicted as wet and 0 otherwise. In this way  $P_i^{flood}$  will be 1 for pixels predicted as wet in all simulations, 0 for pixels dry in all simulations and values around 0.5 will indicate maximum uncertainty.

This method has also been used by Bates et al. (2004) and Mason et al. (2009) to analyse flooding likelihoods on the River Severn and River Thames respectively; Purvis et al. (2008) to produce a weighted map of inundation probability due to uncertain future sea level rises; and Leedal et al. (2010b) as a way of communicating uncertainty in flood forecasts. Bates et al. (2004) comment that a global measure of model performance is preferable to scoring against critical sections of the flood plain. The reasons given by Bates et al. are that a global measure requires no prior assumptions about the hydraulics of the flood, the quality of the observations or the spatial sensitivity of the model. Notwithstanding the attractiveness of this objectivity, one of the objectives of this project is to ascertain whether the additional effort invested in fulfilling these prior assumptions is repaid by a reduction in uncertainty of the predictions in the high risk (or critical) sections of the flood plain.

Maps of  $P^{flood}$  across the domain along with an outline of the observed flood extent will give an indication of the areas where the models perform well and poorly and where the uncertainty amongst the models is greatest (see Aronica et al., 2002 and Bates et al., 2004 for examples). One use of this information is to explore the possibility of implementing a distributed parameterisation of the domain; it may be clear from a highly spatially variable model performance that the use of a single lumped value for channel or floodplain friction may be inappropriate, as noted by Aronica et al. (2002).

### 3.7 Sensitivity Analysis

It is useful to assess how the variation of the output of a model depends on the variations of the input parameters. This allows the modeller to establish how sensitive the model is to uncertainties in the input parameters and whether the behaviour of the model becomes indeterminate for physically realistic parameter settings. In addition, by definition distributed models have many input and output variables which can make the problem of defining the 'behavioural' subset of the parameter space intractable (Beven, 2010). It may therefore be necessary to reduce the dimensionality of the parameter space. The application of 'expert' or 'local' knowledge can achieve great simplifications, for instance by lumping distributed variables into a single value. But carrying out a sensitivity analysis prior to any uncertainty analysis may provide further gains by highlighting which of the remaining parameters and boundary conditions have a significant effect on model output (Beven, 2010). As Saltelli (2000) points out, experience suggests that only a few parameters will be found to have a significant effect on model output.

The simplest form of analysis, point sensitivity analysis or local sensitivity analysis (LSA) involves establishing the local gradient at a point in the parameter space. Analytically, Beven (2008) defines the sensitivity index  $SI$  for parameter  $i$  as:

$$SI_i = \frac{dP/dx_i}{x_i} \quad (3.15)$$

Where  $x_i$  is the local value of the parameter and  $P$  is the predicted variable (model output). Typically the gradient term  $dP/dx_i$  is evaluated numerically by measuring  $P$  from many model runs where  $i$  takes slightly differing values. LSA may give some indication of structural problems with the model, and an idea as to which parameters have first order significance but there are many issues that will not be exposed by LSA. These issues are commensurate with the factors driving the adoption of uncertainty analysis methods such as GLUE: equifinality of model output suggest that interactions between 2 or more parameters are influential on the model output (Cloke et al., 2008); the choice of output variable  $P$  will significantly influence the sensitivity index values for the parameters (Beven, 2008). Furthermore, the sensitivity analysis method itself

has been shown to influence the apparent sensitivities of the model to different parameters (for example see Borgonovo, 2006; Pappenberger et al., 2006b). So to address these issues a generalised approach to sensitivity analysis is required, these methods, often known as Global Sensitivity Analysis (GSA) are detailed in several books and papers (Cloke et al., 2008; Ratto et al., 2001; Saltelli, 2008).

### 3.7.1 Sensitivity analysis of distributed parameters

As mentioned earlier in section 3.2.2 Manning's  $n$  for the river channel and the floodplain are seen as important factors in modelling floods and are frequently employed as effective parameters to compensate for model simplifications. It is common to test the sensitivity of flood models to these parameters for both rural (Aronica et al., 2002; Horritt and Bates, 2001a; Horritt and Bates, 2001b; Werner et al., 2005) and urban (Fewtrell et al., 2008; Mignot et al., 2006) flood events. Sensitivity analysis of urban flood models can be particularly important where the grid resolution and implementation of sub-grid scale topographical features can have important, often unpredictable, effects on the model output (Mignot et al., 2006; Neal et al., 2009; Yu and Lane, 2006a).

It is not always the case that Manning's  $n$  for channel and floodplain are given just one lumped value each. Schubert et al. (2008) defines a friction value for each model cell based on land-classification from aerial imagery, thus the friction values are no longer 'effective' representations and should be considered input data rather than model parameters.

A compromise is to apply a semi-distributed approach where the floodplain is divided into a number of zones, each with a different Manning's  $n$ . Werner et al. (2005) use land classification to divide the floodplain into zones with five different friction values. A semi-distributed approach is also taken by Mignot et al. (2006) who divides Nîmes, France into 3 zones based on street layout and analyses the parameter sensitivity in each zone as well as across the whole domain. This is similar to the approach taken by Neal et al. (2009) who divide the city of Carlisle, UK into 4 zones to reflect the differing urban fabric and also the distribution of available calibration data. Hunter et al. (2005a) and Hall et al. (2005a) find little sensitivity to floodplain friction,

so use a single value across the domain, but split up the channel friction into 3 and 4 zones respectively. Hall et al. (2005a) then analyse the sensitivity for each of the 4 zones and find that, although the channel friction remains the most important in all zones, the sensitivity of the model to floodplain friction increases in a downstream direction (probably due to the increasing width of the floodplain). The approach taken by Pappenberger et al. (2007b) is to divide the domain into 7 zones and investigate the model performance in each zone, finding significant variation in model performance and parameter sensitivity between the zones. Schumann et al. (2007b) find it sufficient to divide their model domain into two in order to generate locally acceptable models.

### 3.8 Risk based calibration

The distributed nature of 2D flood models such as LISFLOOD-FP pose a particular problem to modelling where it is possible to define model facts such as Manning's  $n$  for each individual cell, but it is far from feasible to carry out a sensitivity analysis or calibrate the model whilst varying factors at the individual cell level. The studies cited in section 3.7.1 show that splitting a model into sub-domains can expose significant variation in model performance and sensitivity within the domain (Hall et al., 2005a; Pappenberger et al., 2007b). Hall et al. (2005a) suggest areas in the model domain identified as particularly influential in terms of model performance could be targeted for more detailed analysis, either in the form of data acquisition or nesting of higher resolution models. However Hall and colleagues fall short of recommending calibrating the model to a distributed parameterisation. Conversely, Pappenberger et al. (2007b) embrace a subjective approach to model calibration by suggesting a vulnerability weighted measure of model performance,  $L(v)$ :

$$L(v) = \frac{\sum_i v_i S_i}{n} \quad (3.16)$$

Where  $v_i$  is the vulnerability weight of cell  $i$ ,  $n$  is the number of cells included and  $S$  is a cell based measure of model performance, for example the standard similarity function of Hagen (2003) (see Pappenberger et al. (2007a) or a full description). From this, in a similar way to calculating  $P_i^{flood}$  in equation 3.14, a vulnerability weighted flood probability,  $P(v)_i^{flood}$  is given by:

$$P(v)_i^{flood} = \frac{\sum_j f_{ij} L(v)_j}{\sum_j L(v)_j} \quad (3.17)$$

Where  $f_{ij}$  is the binary state of the cell  $i$  in simulation  $j$  (wet = 1, dry = 0). Pappenberger et al. (2007b) employ simple methods based on land use, building types and transport links to define the vulnerability weighting of the cells, but the concept can easily be employed using other, more complex, weighting schemes. However, the subjective process of identifying the flood prone areas where the consequences of flooding are greatest will expand the role of the modeller beyond pure physical science into the realm of social science. In comparing the vulnerability weighted performance measures against a global performance measure Pappenberger et al. (2007b) find considerable variation, but go on to note that calibrating against a limited subset of the domain increases the likelihood of over-fitting the model to particular areas. Not only can this cause a reduction in the overall model performance, but may introduce bias for future flooding events which are likely to be characterised by significantly different parameterisations (Romanowicz and Beven, 2003). Chapter 5 describes the application of a risk based calibration scheme to the model of the January 2005 flood in Carlisle.

## Chapter 4. Uncertainty in point observations

### 4.1 Introduction

This chapter has been published as a journal article titled “Reducing inconsistencies in point observations of maximum flood inundation level” under the authorship of Parkes et al. (2013) in the journal *Earth Interactions*. The figure, table and equation numbers have been changed to be consistent with the rest of the thesis, but the text is largely unaltered from the published article. ©Earth Interactions. Used with permission.

With the shift to more risk-based approaches to managing flooding, flood hazard maps and simulation models have assumed new prominence as instruments for informing policy decisions about the regulation of land use and spatial planning, pricing and availability of flood insurance, and the allocation of resources for flood defence schemes. With so much at stake in those decisions, it is important to reduce the uncertainties associated with scientific assessments of flood risk and inundation extent, not least because they provide grounds for political controversy over risk management decisions (Porter and Demeritt, 2012).

To that end flood inundation modelling provides vital information to help assess the risk of future flood events, the effectiveness of proposed defence schemes, such as dikes and levees, and the potential consequences of their failing (Dawson et al., 2005; Porter, 2010).

While improvements in computing power and in the accuracy of digital elevation models have made it possible to simulate urban flooding using high resolution (<10 m) two dimensional (2-D) flood models (Dottori and Todini, 2012; Smith et al., 2006), they have also increased the relative significance of observational uncertainties of flooding extent. 2-D flood models have now advanced to the stage that it is possible to simulate large scale urban floods at a resolution high enough to realistically represent the physical processes affecting both the extent and dynamics of flooding in complex, built-up areas (Bates, 2012), which are particularly important to understand given the great risks to life and property posed by such urban flooding.

2-D flood models apply a variety of approaches to estimating solutions of the shallow water equations defined by Saint-Venant (1871). Reviews of commonly used models can be found in Hunter et al. (2008) and Pender and Néelz (2010). The model used for this research, LISFLOOD-FP, divides the floodplain into a regular 2-D grid of storage components (Bates and De Roo, 2000) and uses a simple wave representation that includes diffusion and inertia to simulate floodplain flow between cells (Bates et al., 2010). One of the motivating factors driving the development of LISFLOOD-FP is the desire for a physically-based model that can take advantage of high-resolution floodplain DEM data, using the simplest possible process capable of describing 2-dimensional dynamic flood inundation (Bates and De Roo, 2000). This is justified on the basis that simplification of the physical process can be compensated for through the use of effective parameters to represent channel and flood plain friction (Horritt and Bates, 2001b). The benefits of this approach are that the model is simple to set up, computationally efficient and easy to integrate with third party GIS systems (Bates and De Roo, 2000), although, as is generally the case with 2-D flood models, calibration against observational data is necessary before the model is able to make accurate predictions (Horritt and Bates, 2002).

Despite efforts to make them physically realistic, 2-D models necessarily involve some parameterisation and even if the parameters are physically-based, they will not be accurate representations of reality (Beven, 2008). Observational data of previous flood events in the model domain are required to calibrate the model in the hope of identifying the parameters sets which give rise to a useful representation of reality (Hunter et al., 2005a). However the nature of floods are such that a parameter set that accurately simulates one flood may not be representative for subsequent flood events of a different magnitude. Since extreme flood events are, by definition, rare and difficult to access safely, the observational data available is always limited.

There is a variety of different sources of data on flood inundation extent, marked by their own limitations. Recordings of water levels from river gauges in or near the affected area can be a valuable source of point data, especially if they produce frequent and reliable readings of water level. However the utility of river gauge readings in model calibration can be limited: they only provide water level readings



within the channel and so cannot inform the model on water extent across the floodplain; they are often known to become unreliable at times of out of bank flow (Brakenridge et al., 1998); and they are often used to provide the data for the inflow (and outflow) boundary conditions of the hydraulic model itself (for example see Neal et al., 2011).

Surveys to collect remotely sensed imagery of the extent of the flood are an extremely valuable source of observational data, especially for 2-D models where the image can not only be used as a global calibration dataset of the model domain but also as a source of information for understanding and improving the model structure (Schumann et al., 2009). Prior to the invention of digital imagery, aerial photography has been used for the purposes of flood assessment since the early 20th century (Bhavsar, 1984). Even before the widespread use of computerised image processing, a skilled analyst could use information on aircraft height, camera specification, image size and angle to accurately measure the spatial extent of flooding (Marcus and Fonstad, 2008). Although aerial photography remains potentially the most accurate method of measuring flood extent remotely, the costs and logistics of rapidly commissioning airborne surveys, their dependence on fine weather, the difficulty of orthorectifying and building a mosaic from the images and the requirement to manually identify water extents all conspire to limit their use.

Satellite remote sensing is increasingly being used to fill that gap in observational data (Schumann et al., 2009). Images from synthetic aperture radar (SAR) have often been used in the UK and elsewhere for monitoring floods (see for example Biggin, 1996; Dung et al., 2011; Horritt et al., 2001; Hunter et al., 2006; Mason et al., 2009; Matgen et al., 2010) and sophisticated algorithms have been developed to extract the water outline automatically (Mason et al., 2009; Schumann et al., 2007a). In spite of complications such as double-bounce reflections from buildings the high resolution SAR images from recently launched satellites such as TerraSAR-X is approaching the accuracy of aerial photos even in inundated urban areas (Schumann et al., 2011).

These limitations with conventional scientific instrumentation have spurred efforts to find alternative sources of data. For example Connell et al. (1998) interviewed 40

residents directly affected by floods of the Waiho River, New Zealand in 1986 and 1994. As well as the descriptions of maximum flood levels, residents also provided photos and videos. Interpretation of the images was hampered by the oblique angle of the photos and lack of information on the time the images were taken, but Connell et al. estimate the water depth accuracy to be within  $\pm 0.2\text{m}$ . The recent expansion of digital cameras, videos and mobile phones with cameras, means there are now likely to be extensive photographic records of floods with timestamps, and the popularity of on-line image sharing sites such as Flickr eases the process of data collection. After a flood at Morpeth, UK in September 2008, Parkin (2010) used almost 1,500 pieces of information to build a series of hourly snapshots of the rising limb of the flood.

Instead of interviewing eye-witnesses or collecting their photographs, post-event surveys in the immediate aftermath of flooding can also seek to identify and map signs of the recent flood, either in the form of water marks (stains on vertical surfaces such as walls), or wrack marks (lines of debris deposited on the ground by the water as it begins to recede) (see figure 4.1). Whilst it is possible to identify high water marks from remotely sensed images of high quality and resolution (for example see Lane et al., 2003; Stephens and Bates, 2015), local surveys are considered less uncertain (Stephens and Bates, 2015). Local surveys of wrack marks using hand-held global positioning system (GPS) devices allow for straightforward recording of the horizontal location of high water marks that can subsequently be intersected with the DEM to give the location in the vertical (Schumann et al., 2007b); the accuracy of this method is dependent on the local topographic slope as well as the precision of the GPS measurement. More recently, the emergence of differential GPS (dGPS) devices allow direct, in situ vertical measurements of the elevation of water and wrack marks accurate to within 0.01 m (Horritt et al., 2010), although the accuracy of those marks as measures of the water height itself may not be quite so precise. For example the surveyor may miss the peak deposition line, or the surface may retain marks higher than the extent of the water caused by upward diffusion of the deposition surface. Often these high water mark data are used as a supplement to more conventional sources of flood extent data (Hunter et al., 2005a; Schumann et al., 2007a), but sometimes data from extensive surveys have provided the primary data source for

model calibration: Mignot et al. (2006) used a set of 99 high water marks on buildings in the town of Nîmes, France, to calibrate a model of a severe flood in 1988; a small, but destructive flood in Boscastle, UK in 2004 was modelled by L'homme et al. (2010) using a survey of 72 wrack marks for model validation; the aftermath of the flood in Carlisle, UK, January 2005 was extensively surveyed by two independent teams giving rise to a dataset consisting of 217 wrack marks and 46 water marks. In the absence of any remote sensed images of the flood, the data from the surveys has been used as the primary source of calibration data for several projects modelling the event (Fewtrell et al., 2011b; Horritt et al., 2010; Leedal et al., 2010b; Neal et al., 2009).

The dataset from the 2005 Carlisle flood is the focus for the analysis presented in this paper. Some analysis of the accuracy and characteristics of the wrack and water marks was performed by both Neal et al. (2009) and Fewtrell et al. (2011b). Neal et al. (2009) found evidence that wrack marks underestimate the peak water level when compared to water marks by 0.51 m on average, a difference they attributed to some combination of the surveyor missing the highest wrack mark in locations where multiple depositions of debris occurred due to the receding waters remaining stationary for multiple periods and, in the case of water marks on buildings, the staining may be higher than the actual water level due to capillary action. Fewtrell et al. (2011b) went further with their analysis, not only comparing wrack and water marks against each other, but also with the peak water height recorded by a nearby river gauge. They suggested the mean difference between proximate observations to be 0.1 m, which is within the accuracy of the DEM, although they did find greater average differences when comparing wrack marks to water marks (Fewtrell et al., 2011b).

Other than the examples of Neal et al. (2009) and Fewtrell et al. (2011b), both from the 2005 Carlisle event, it seems there has been little or no effort to systematically measure the uncertainty in wrack and water marks as measures of maximum flood extent and depth. Apart from the lack of reference data against which to measure the wrack marks, this is also perhaps because other uncertainties in flood models, or indeed the accuracy of the DEM itself, were thought to dwarf inaccuracies in physical records of the water extent. However, as highly accurate LiDAR surveys become more

widely available and the resolution of 2-D models increases, the uncertainty of the measurements will become relatively more significant (Bates, 2012).



Figure 4.1. A wrack mark of debris deposited by a flood near Tewkesbury, UK. Photo taken 3rd May 2012.

The purpose of this paper is to assess the inaccuracies associated with observational datasets from locally surveyed wrack and water marks and to propose a ‘smoothing’ algorithm that can be used both to facilitate the identification of specific errors and for reducing overall observational uncertainty. The paper is organized as follows: in the following section (4.2) the study event and datasets are introduced. Next, in the methods section (4.3) the smoothing algorithm is described and applied to the dataset, the results of which are shown in section 4.4. Finally conclusions are drawn on the applicability of the method and its potential benefit to flood inundation modelling.

#### 4.2. Case Study: January, 2005 River Eden flood at Carlisle, UK.

Carlisle is a town in Cumbria, North West England with a population of approximately 100,000. The town was an important Roman settlement established to serve forts on Hadrian’s Wall, remnants of which still stand in the town today. Carlisle

is located on the River Eden with two notable tributaries, the Caldew and the Petteril, joining the Eden at Carlisle (see figure 4.2). The catchment area of the River Eden and its tributaries is largely in the English Lake District, a national park with the highest annual rainfall in England (Barker et al., 2004).

In January 2005, up to 175mm of precipitation fell in the Eden catchment over a period of 36 hours (Fewtrell et al., 2011b). This resulted in an estimated 1 in 200 year flood event in Carlisle (Mason et al., 2007b) with approximately 1,800 homes inundated (Day, 2005a). The peak discharge on the Rivers Caldew and Petteril preceded that of the Eden and it was these tributaries that first reached out of bank conditions at approximately 02:00 on 8th Jan in the Denton Home, Caldewgate and Botcherby Bridge areas of Carlisle, the flooding exacerbated by blockages from debris (Day, 2005a; Environment Agency, 2005). The River Eden overtopped its defences several hours later at approximate 08:30, and there followed significant backwatering effects along the main tributaries (Day, 2005a; Environment Agency, 2006).

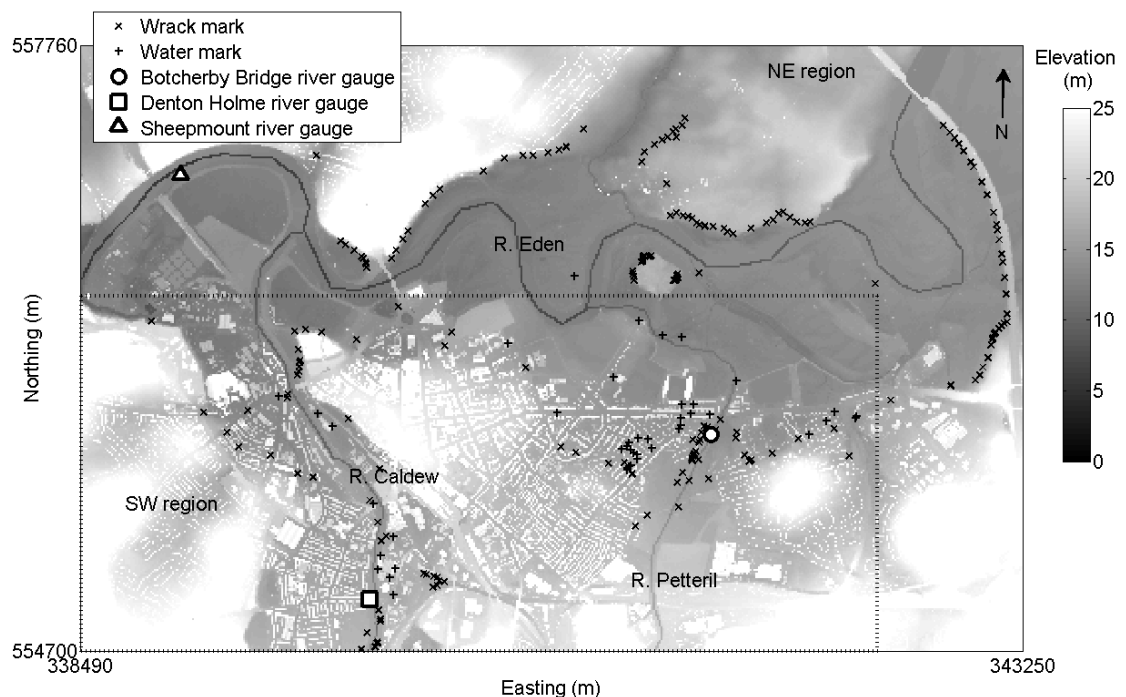


Figure 4.2. Digital elevation map of Carlisle, UK showing the main water courses, locations of river gauges and observations of maximum water extent from records of wrack marks (x) and water marks (+). The dotted line delineates the SW, largely urban, subset of wrack and water marks from the largely rural subset in the NE.

In the weeks following the flood, two post event survey teams, from the University of Bristol and the Environment Agency identified visible evidence of the maximum extent and/or depth of the flood waters and measured and recorded their locations using Differential Global Positioning Systems (dGPS). The dGPS locations were recorded relative to a temporary base station within the study area, which had been located relative to a nearby Ordnance Survey maintained reference point (Horritt et al., 2010). Horritt et al. (2010) estimate the accuracy of the devices to be within  $\pm 0.01$  m, and although this has not been verified by the authors, it is consistent with figures quoted for comparable surveys (for example Rayburg et al., 2009). Six river gauges are in or immediately upstream from the study area- the locations of three of these gauges are marked in figure 4.2. Ideally the inflow boundary conditions for the three rivers would be provided by data from the upstream gauges. However the upstream gauges on the Eden and the Caldew were known to be unreliable, so new ratings had to be derived for these gauges from a separate modelling exercise (described in Horritt et al., 2010). It is these new ratings that were used here to derive the upstream boundary conditions for the Eden and Caldew; the resulting hydrographs from the three rivers are shown in figure 4.3. Some of the most destructive flooding occurred alongside the Caldew where initial flooding was likely to have been caused by partial channel blockage by debris at a footbridge. This was followed by significant backwatering up the Caldew channel as the main flood wave on the Eden arrived (Environment Agency, 2005).

### 4.3. Methods

#### 4.3.1 Analysis of wrack and water marks in Carlisle

As mentioned in the introduction, both Neal et al. (2009) and Fewtrell et al. (2011b) provided estimates of the accuracy of the wrack and water marks surveyed in Carlisle after the January 2005 flood. Neal et al. (2009) restricted their analysis to a comparison of the only area where multiple wrack and water marks were located within 100 m of each other. From this limited subset, 2 wrack marks were compared to 4 water marks giving a mean discrepancy of 0.51 m (Neal et al., 2009). Fewtrell et al. (2011b) carried out a more extensive analysis comparing all wrack and water marks that are within 500 m of each other and also making comparisons against readings

from the river gauge at Botcherby Bridge which is located within a dense cluster of wrack and water mark observations (see figure 4.2). They conclude the mean difference between true peak water levels and wrack/water mark measurements to be approximately 0.1 m. Here we build on the work by Fewtrell et al. (2011b) firstly comparing observations not just with other, individual observations, with the average of a set of nearby observations. This not only allows us to estimate the internal uncertainty in the set of observations, but also pinpoint individual measurements that are particularly inconsistent and later, in section 4.3.2, we propose a smoothing algorithm for reducing those inconsistencies.

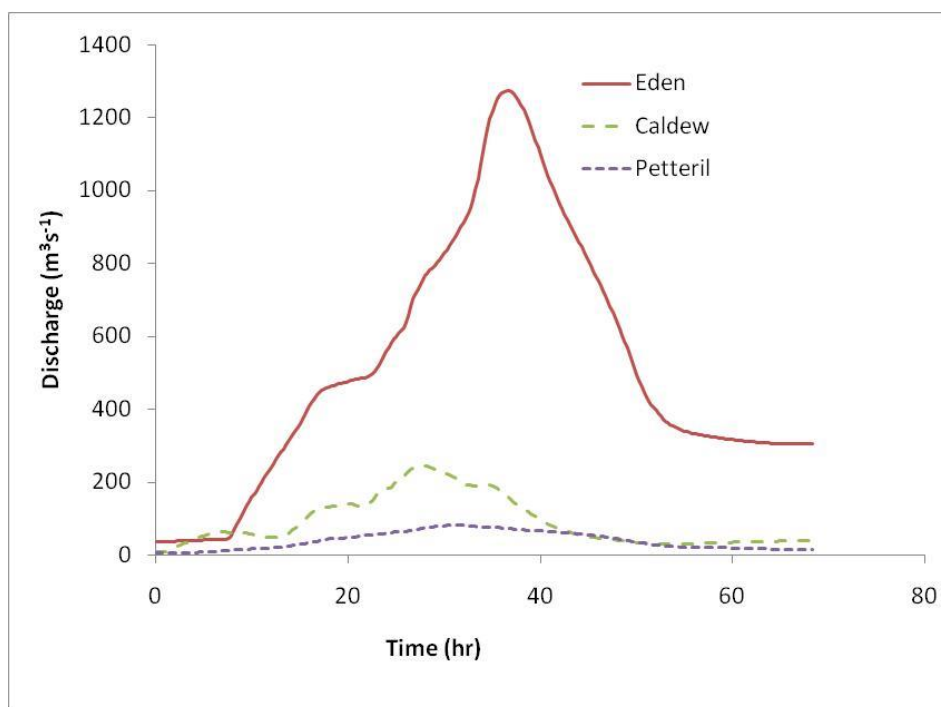


Figure 4.3. Hydrograph of the 3 main watercourses in Carlisle at the time of the January 2005 flood. The start time of the hydrograph is 00:45 on 7 January 2005.

We analyse each observation by identifying the 10 nearest neighbours (10nn) to that point and comparing the recorded height of the point with the mean height of the 10nn. The results can be seen in figure 4.4.

Figure 4.4 (a) shows data for all 263 observational data points. Little information can be gained from the points that are clearly isolated from their neighbours (i.e.

where the mean distance to the 10nn is greater than 200-300 m). For these points the height difference shows considerable variation here, as is expected because no account is taken of water slope between neighbouring observations. When the observations are in closer proximity there is less variation, but several points stand out by showing discrepancy in height of over 0.5 m with a mean distance of less than 100 m to their 10nn. This difference is unlikely to be accounted for by water slope alone which would be expected to be between 0.0001 and 0.001 m/m (0.01 to 0.1 m per 100 m) (Mason et al., 2007a), indeed Horritt et al (2010) estimate the slope at Carlisle to vary between 0.00025 and 0.0006 m/m. However, it cannot necessarily be concluded that any larger discrepancy shown by wrack and water marks must be due to inaccuracy in the reading: in this event, peak water heights are likely to be influenced by small scale hydraulic effects in the built up areas or where waterways become blocked by debris, as was the case on both the Petteril and Caldew (Environment Agency, 2005). In order to provide a simple visual summary, figure 4.4 (b) shows the mean absolute height differences collected into 50 m bins. The mean absolute height difference for all measurements where the mean distance of less than 100 m to their 10nn is 0.105 m, an estimate of uncertainty which is consistent with the figure of 0.1 m estimated by Fewtrell et al. (2011b). The mean height difference can be seen to increase in areas where the observations are more sparse (greater mean distance to 10nn) and the effect of the slope of the water is likely to have more influence.

As can be seen from figure 4.2 many of the wrack marks were collected beyond the north and eastern banks of the Eden away from the urban areas affected by the flood. In these areas the water level is likely to vary smoothly with little small scale variation, and there are many wrack marks in close proximity. To explore this effect, figure 4.5 splits the data point into 2 zones; the NE where all the observations are in rural locations and the SW where many of the observations are in built-up, urban areas (see regions in figure 2). It is clear that the variations in observations are greatest in the urban areas. The explanation is less clear: there may well be more highly localised spatial heterogeneity in maximum water depth; alternatively measurement errors may be higher in the urban area (Horritt et al. (2010) point out that difficulties of obtaining



GPS measurements next to buildings due to poor satellite coverage); the observations in NE are, with one exception, all wrack marks, whereas the observations in the SW are a more heterogeneous mix of wrack and water marks, any bias between the two types of observation will manifest itself as a greater variation observation heights.

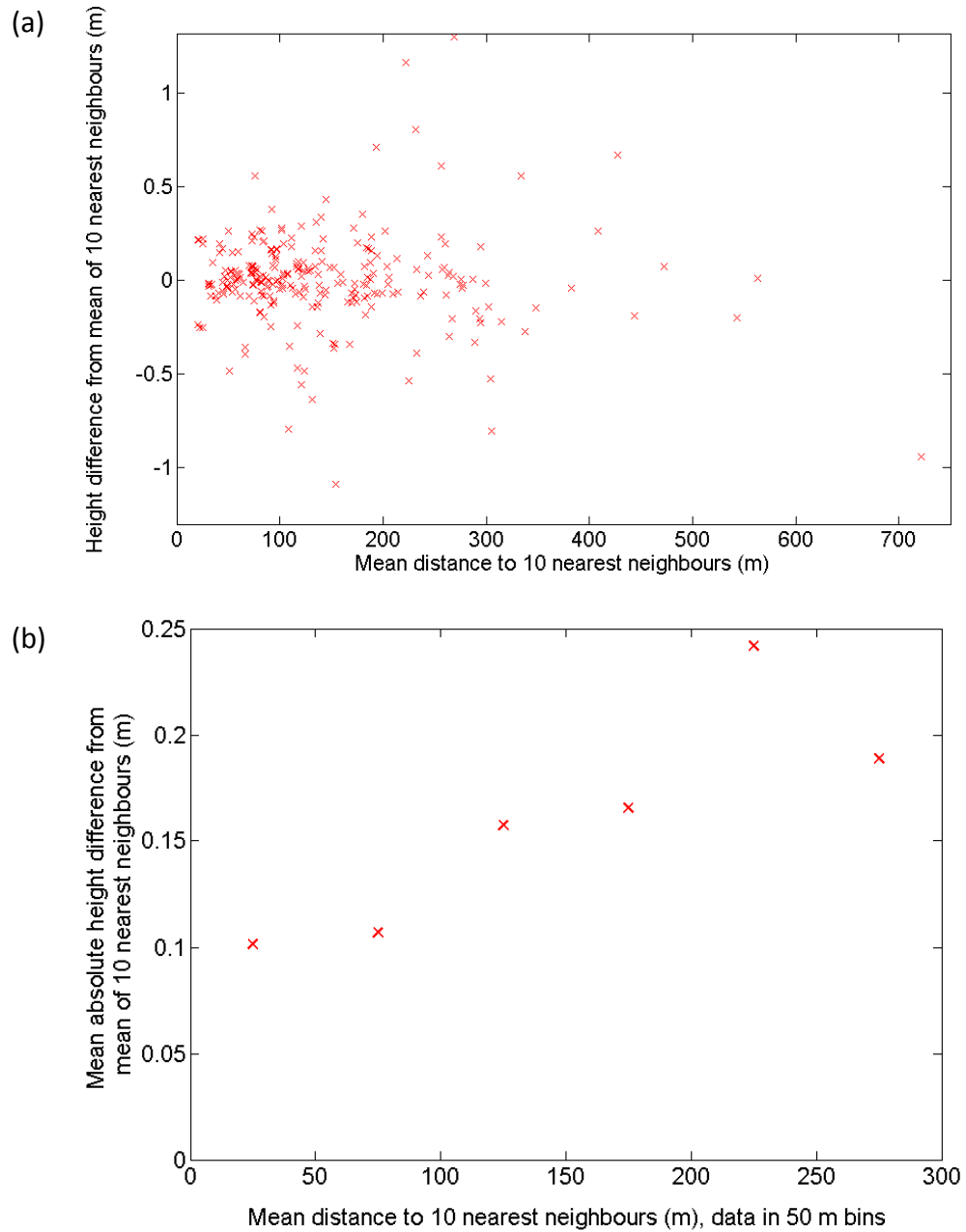


Figure 4.4. (a) For each observational data point, difference between recorded height of data point and mean height of the 10 nearest neighbours (10nn) plotted against mean distance to the 10nn. (b) Mean absolute height difference between data points and their 10nn, collated into 50 m bins.

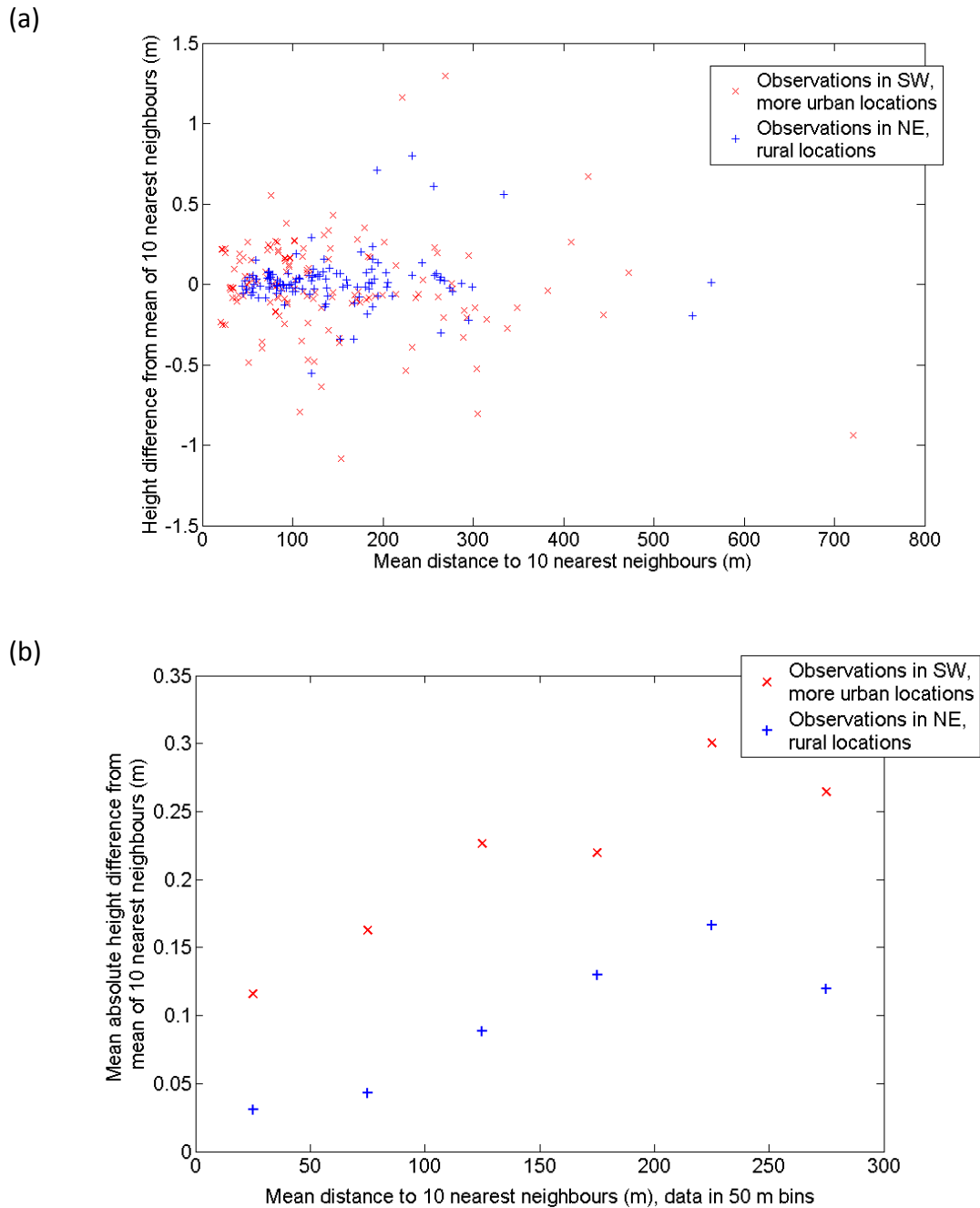


Figure 4.5. (a) For each observational data point, difference between recorded height of data point and mean height of the 10 nearest neighbours (10nn) plotted against mean distance to the 10nn. (b) Mean absolute height difference between data points and their 10nn, collated into 50 m bins. Observations split between those to the north and east of the study area (in rural locations) and those in the south and west, in more urban areas.

#### 4.3.2 Proposed smoothing algorithm for improving the accuracy of water and wrack mark readings.

In this paper we propose a 'smoothing' algorithm which can either be applied to the raw dataset to attempt to reduce inconsistencies between neighbouring observations, or it can be used to identify the most inconsistent data points which the researcher may then decide to exclude from the dataset. The proposed smoothing algorithm differs somewhat from a suggestion made previously by Neal et al. (2009) to run multiple interpolations, missing out one measurement each time to identify outliers that may have large errors. The analysis above suggests there aren't many instances where an obvious outlier could be identified, particularly in the urban areas where most of the variation in observation height occurs. Instead an algorithm has been developed that adjusts each reading by an amount that is influenced by a number of its geographically nearest neighbours. The influence that any one reading has on another is affected by the geographical separation of the readings and the variance between the influencing reading and the mean height of its nearest neighbours. The physical basis for attempting to 'smooth' the observations in this way is the assumption that water level slopes at this stage of a river are low (Mason et al., 2007a) so the peak water level should not vary on a short spatial scale as much as the raw data suggests. It is acknowledged that the hypothesis that the maximum flood level will vary smoothly is more likely to be true in open, rural topography, whereas maximum flood levels in urban areas or near infrastructure such as bridges and man-made culverts may well show greater variation due to the hydraulic effects of the constructions. This point is addressed in the results section by comparing the effects of the smoothing algorithm in urban and rural areas and by analysing the effects of the algorithm on individual observations near a large bridge.

The smoothing algorithm is a two stage process involving three parameters described in table 1 which can be tuned using a process described in section 3.3.

The algorithm works by first calculating a 'validity weighting' for all the observations in the set of wrack and water marks. Each mark -  $M$  is given a validity weighting  $V$

between 0 and 1, which is calculated from the mean of the difference between the water height as recorded at M and the recorded water heights of the set of nearest neighbours (nn) to M ( $\overline{\Delta h}$ ). If the absolute value of  $\overline{\Delta h}$  is greater than the validity cut-off (vh), the reading is not deemed to have an influence on neighbouring points and is assigned a validity weighting of zero. Otherwise the validity weighting of point M ( $V_M$ ) is given by:

$$V_M = 1 - (1/v_h |\overline{\Delta h}|) \quad (4.1)$$

It should be noted that the validity weighting is not necessarily a measure of the validity or accuracy of the reading, just a measure of the validity of using the reading as an influence on its neighbours.

Table 4.1 Parameters used by the smoothing algorithm.

Parameter	Description	Default value
<b>Nearest Neighbours (nn)</b>	The maximum number of neighbours that can influence each data point	10
<b>Validity cut off (vh)</b>	Determines the influence each point has on its nearest neighbours.	0.5 m
<b>Alpha (<math>\alpha</math>)</b>	Determines the rate at which the influence of a point decreases with increasing distance	100

Next, the proposed adjustment C is calculated for each observation M from its nearest neighbours such that:

$$C_M = \frac{\sum_{i=1}^{nn} \Delta h_i V_i \left(1/(1+d_i/\alpha)\right)}{\sum_{i=1}^{nn} \sqrt{V_i \left(1/(1+d_i/\alpha)\right)}} \quad (4.2)$$

where  $d_i$  is the distance from  $M$  to its  $i$ th nearest neighbour and  $\alpha$  is a scaling constant that determines how the influence of one point on another decreases with distance. A figure of 100 for  $\alpha$  means that a separation of 100 m between two points will reduce the influence the points have on each other by 50%. Section 4.3.3 describes how the parameter can be tuned to select values suitable for the specific dataset.

#### 4.3.3 Tuning process for smoothing algorithm

The process for selecting suitable parameter values for the three parameters used by the smoothing algorithm involves multiple simulations of sets of point observations of a known, ideal water surface. For each simulation, a number of data points are randomly selected from the ideal water surface and their heights are given a random perturbation away from the height of the water surface.

Several aspects of the simulation can be chosen to match the actual study area. For example, in order to select algorithm parameters appropriate for the observational dataset from the January 2005, Carlisle flood, 263 data points were simulated across a rectangular area of 4760 m by 3060 m. The simulated water slope was 0.001 m/m which is the upper end of the range suggested in section 4.3.1; this was considered suitable due to the presence of smaller tributaries and urban inundation which are likely to give rise to steeper water gradients in some areas. The simulated data points were randomly perturbed by an amount following a normal distribution, mean 0, standard deviation 0.105 m to match the estimate of observational uncertainty calculated in section 4.3.1. Each simulation was scored on the basis of how much the root mean square error (RMSE) of the perturbed, simulated data points was reduced after applying the smoothing algorithm. After running a Monte Carlo simulation, the default values for the parameters given in table 4.1 were deemed suitable for the Carlisle, 2005 observational dataset. A first order sensitivity analysis using the method described by Saltelli et al. (2008) suggest the performance of the algorithm is most sensitive to  $nn$  (see table 4.2).

Table 4.2. Sensitivity indices of the model to the 4 parameters varied on the Latin Hypercube sample

Parameter	First order sensitivity index (Si)
Nearest neighbours (nn)	0.250
Validity cut off (vh)	0.082
Alpha ( $\alpha$ )	0.202
Total first order sensitivity	0.534

#### 4.4. Results

When this algorithm is applied to the dataset of 263 wrack and watermark readings collected after the 2005 Carlisle flood, the mean absolute change to the points was 0.0823 m with a maximum increase in height of 0.5951 m and a maximum decrease of 0.5938 m. To a certain extent the assessment of the value of these results is a subjective choice to be made by the researcher. It may be that the results are just used as a guide to identify the most incongruous data points that should be considered for removal. Here the results of the algorithm are used to create an alternative, 'smoothed' dataset which is initially assessed for internal consistency (section 4.4.1), then a limited objective assessment is made against river gauge data (section 4.4.2). Finally a comparison is made with the raw dataset by using both data sets to calibrate a 2-D hydraulic model of the flood event (section 4.4.3).

##### 4.4.1 Internal consistency

Figure 4.6 shows the height difference between each point and the average of its 10nn for both the original 'unsmoothed' data and after applying the smoothing algorithm. As expected, figure 4.6 shows the algorithm has a marked smoothing effect on the data, reducing the height variation amongst proximate readings; the mean absolute height difference for all measurements where the mean distance of less than 100 m to their 10nn is reduced from 0.105 m to 0.038 m for the smoothed data. The mean change was 0.0043 m suggesting no significant overall shift in the readings up or down. Figure 4.7 shows the separate effects of the algorithm on urban and rural areas, where, as expected, the variation between proximate readings is seen to be greatest in urban areas.

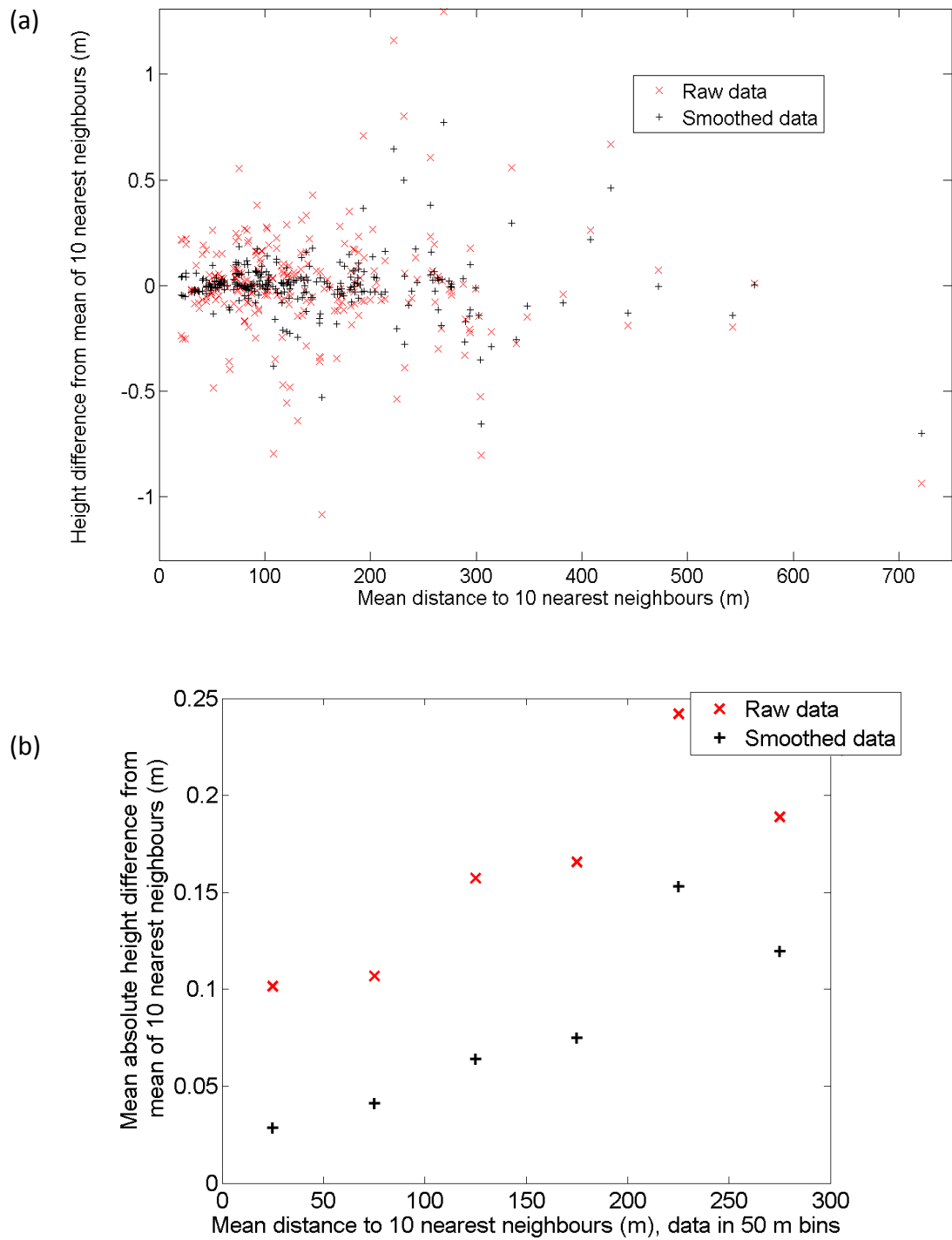


Figure 4.6. (a) For each observational data point, difference between recorded height of data point and mean height of the 10 nearest neighbours (10nn) plotted against mean distance to the 10nn. (b) Mean absolute height difference between data points and their 10nn, collated into 50 m bins. Raw (red x) and smoothed (black +) data.

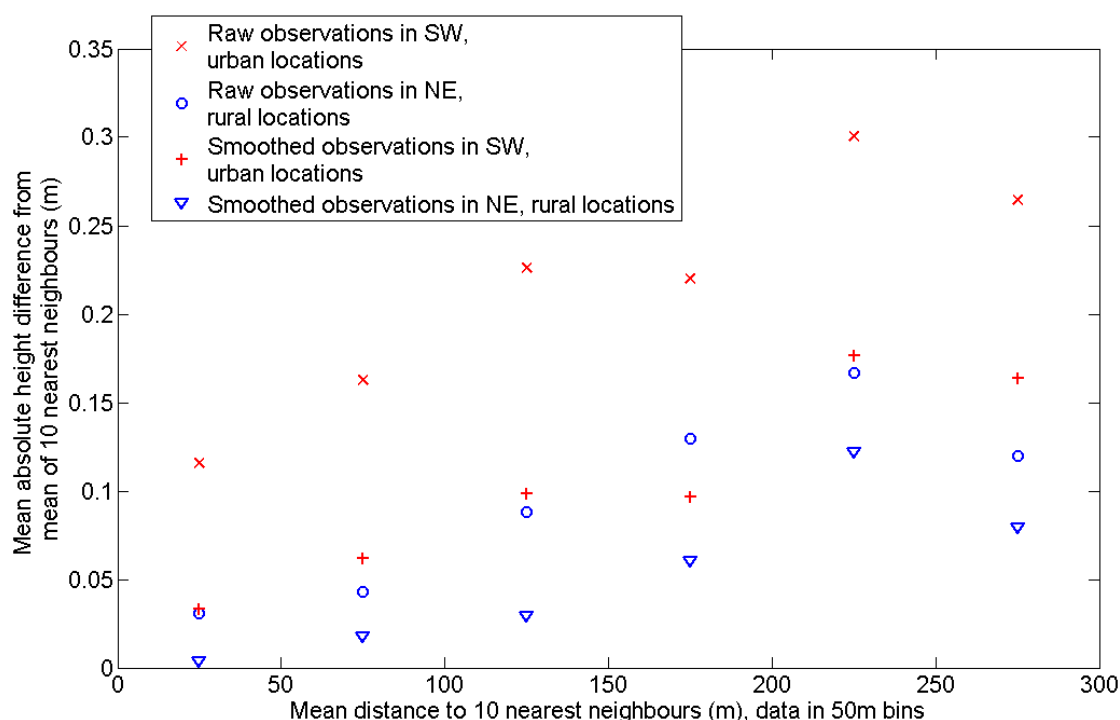


Figure 4.7. Mean absolute height difference between data points and their 10nn, collated into 50 m bins. Observations split between those to the north and east of the study area (in rural locations) and those in the south and west, in more urban areas.

Raw (red x & +) and smoothed (blue circles and triangles) data.

#### 4.4.2 Comparison with river gauge data

As remarked previously, the wrack and water marks form the bulk of the validation data for simulations of this event, so there is not a significant body of data against which to validate the effect of the smoothing algorithm. However, there are recordings of maximum flood levels recorded by the Botcherby Bridge and Denton Holme river gauges (locations marked on figure 4.2), which are both close to a mixture of wrack and water mark observations. Water level readings from river gauges at times of flood are less problematic than the corresponding discharge estimates and the accuracy of the peak water levels is thought to be around 1-2 cm (Di Baldassarre and Montanari, 2010), so comparing the water height observations in the vicinity of the river gauges will help provide an objective indication of their accuracy. Figure 4.8 shows the peak water heights of all wrack and water marks within 250 m of the Botcherby Bridge and Denton Holme gauges. Table 4.3 shows how the mean difference between the peak



water height recorded by the river gauge and the proximate observations is reduced once the smoothing algorithm has been applied. The reduction in height difference between observations and gauge is more marked for Botcherby Bridge, possibly because there are more observations very close to this gauge.

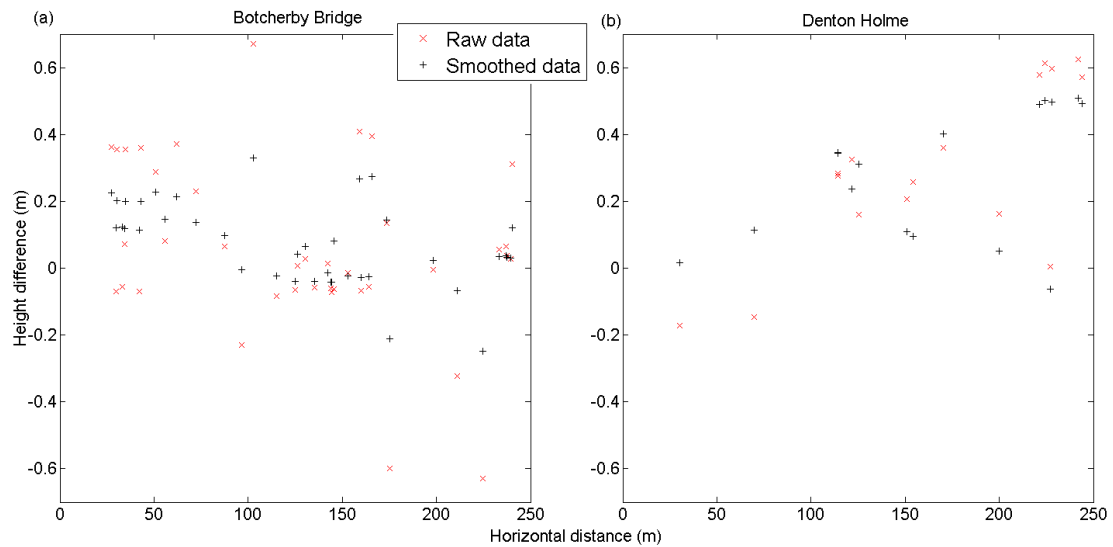


Figure 4.8. Comparison of observed maximum water heights to maximum water height recorded by (a) Botcherby Bridge and (b) Denton Holme river gauges. Raw (red x) and smoothed (black +) data.

Table 4.3. Mean difference between peak water level recorded by river gauges and observations near to the gauges.

Gauge name	Mean absolute height difference (m)		Number of observations
	Raw data	Smoothed data	
<b>Botcherby Bridge</b>	0.18	0.11	40
<b>Denton Holme</b>	0.33	0.29	16

#### 4.4.3 Evaluation using flood simulation data

In this section we evaluate the effects of the smoothing algorithm by comparing the observations against the results of simulations of the flood. This is not an ideal evaluation method and is somewhat self-referential given that flood models are

calibrated using the same raw observational dataset. It is, however, a worthwhile exercise if it highlights limitations in the smoothing method and/or the model calibration process. Whilst simple models based on interpolating surface elevations in the channel sometimes provide useful benchmarks for more sophisticated 2-D models (for example see Mason et al., 2009), in this case the topography and the complexity of 3 separate flood waves in 3 watercourses mean the simple interpolation of water surface elevations does not perform well. As such, the output of a 2-D hydrodynamic flood model of the event is used to evaluate the smoothing algorithm. Here we use the LISFLOOD-FP model developed by Bates and De Roo (2000) with the inertial formulation of the shallow water equations described in Bates et al., (2010) run at 10 m resolution.

The simulations use a digital elevation model (DEM) re-sampled to 10 m from a 1 m horizontal resolution LiDAR dataset of the site. Buildings and vegetation were removed from the LiDAR topology to give the 'bare earth' digital terrain model (DTM), and then the buildings reinserted using digital map data as described in Mason et al. (2007b). The LiDAR dataset has an estimated vertical accuracy of between 0.05 m and 0.15 m (Geomatics Group, 2011). However the post processing required to create the DEM can be problematic in heavily vegetated areas. As a result the root mean square (RMS) error of the DEM is estimated to be 0.18 m (Mason et al., 2007b). (Neal et al., 2012) re-sampled (using the nearest neighbour technique) the DEM to 5m and 10m resolutions and found only minor improvements in model performance ( $< 0.02$  m RMSE) when running at the higher resolution. This is consistent with a point made by Bates (2012): that correct representation of dynamic wetting and drying tends to require a higher resolution than modelling maximum flood extent, as is the case here. For that reason the 10m resolution model was considered sufficient for this study. Here we use the output from a Monte Carlo simulation of 999 model runs to assess the effect the correction algorithm might have when evaluating the flood model. Due to the unreliability of the river gauges discussed in section 2 the discharge figures for the three rivers are varied as part of the Monte Carlo simulation to account for the uncertainty in the upstream boundary conditions. Consequently, the following 5 model

parameters were varied using a Uniform Latin Hypercube Sampling method to generate the 999 parameter sets.

1. Channel Roughness (Manning's  $n$ ) – single global value across the whole model domain, varied between  $0.03 \text{ m}^{1/3} \text{ s}^{-1}$  and  $0.09 \text{ m}^{1/3} \text{ s}^{-1}$
2. Floodplain Roughness (Manning's  $n$ ) – single global value across the whole model domain, varied between  $0.03 \text{ m}^{1/3} \text{ s}^{-1}$  and  $0.09 \text{ m}^{1/3} \text{ s}^{-1}$ .
3. Eden discharge multiplier. A multiplier was applied to all upstream Eden discharge values above a certain base flow level ( $200 \text{ m}^3 \text{ s}^{-1}$ ). The portion of the discharge above the minimum was multiplied by the discharge multiplier. Discharge multiplier was varied between 0.5 and 1.5.
4. Caldew discharge multiplier. A multiplier applied to discharge on the Caldew above a base value ( $15 \text{ m}^3 \text{ s}^{-1}$ ). Discharge multiplier was varied between 0.5 and 1.5.
5. Petteril discharge multiplier. A multiplier applied to discharge on the Petteril above a base value ( $10 \text{ m}^3 \text{ s}^{-1}$ ). Discharge multiplier was varied between 0.5 and 1.5.

The maximum water extent from each simulation was then compared to the water extent as recorded by the observations of wrack and water marks. The location and height of the wrack and water marks are compared to the maximum simulated water levels at the locations of the wrack and water marks. The root mean square errors (RMSE) between the simulated and observed water levels are calculated to give a single score for each simulation. If the simulated water extent does not reach the location of the wrack or water mark, the water level is taken from the nearest point that is inundated in the simulation. This process is repeated for the smoothed observational dataset. Figure 4.9 compares the RMSE using the uncorrected data with the RMSE from the smoothed dataset, it shows that all simulations performing well improve when scored against the smoothed observational dataset. Whilst it cannot be claimed that an improvement in simulations scores necessarily proves that the smoothed observational dataset is a closer representation of reality than the original or 'raw' observational dataset, the universal improvement in RMSE for every simulation with an RMSE of less than 0.6 m strongly suggests some improvement in

the validation dataset. The RMSE for the best performing simulation improves from 0.243 m to 0.187 m, a value very close to the estimated uncertainty in the DEM.

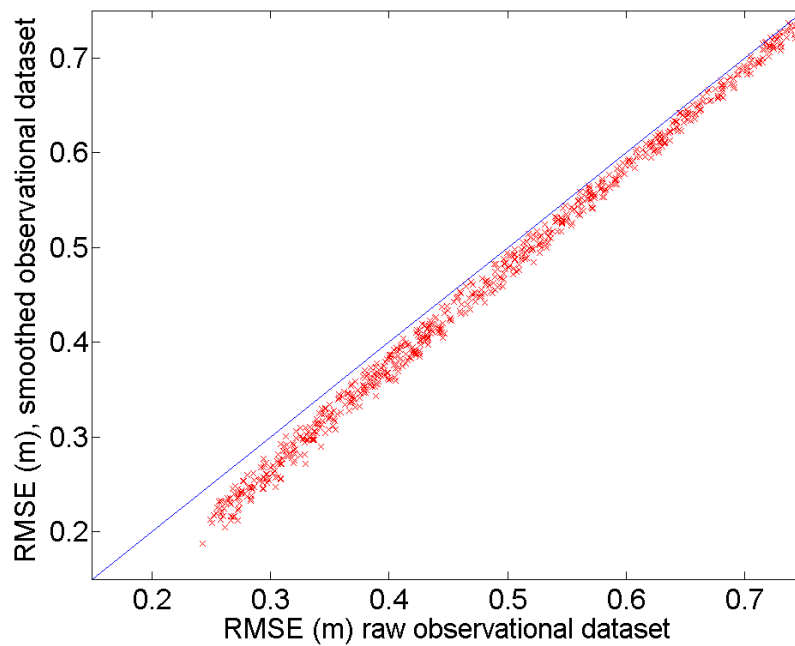


Figure 4.9. RMSE scores for model simulations, raw observational dataset versus smoothed observational dataset.

The correction algorithm is designed to reduce the error in anomalous data points if they are in the proximity of several other points that are roughly consistent, and it will also smooth a series of nearby points if they vary randomly around a mean value. However it is unlikely to identify or correct errors such as any systematic bias that may be present and, as mentioned previously, situations can be envisaged where considerable differences in maximum water height are conceivable over short distances, in which case the smoothing algorithm may be making the observations less accurate. These scenarios are addressed below.

#### 4.4.4 Apparent bias in observations

The physical processes involved in creating a wrack mark or a water mark have not been exhaustively studied and there may be ways that evidence of a high water mark may mislead the observer. Neal et al. (2009) point out that a wrack mark can be left whenever debris laden water sits unchanging for a period, so an observation of a wrack mark may not always correspond to the maximum water extent. Similarly wind

and wave action could push both wrack and water marks above the true maximum water level and, specifically for water marks, capillary effects of the material on which the mark is left could raise the apparent water level (Neal et al., 2009), an example of this effect can be seen in figure 4.10. Occasional, random errors introduced in this way should be effectively corrected by the algorithm proposed above, but there is a suggestion of a non-random systematic discrepancy between the height of water marks and wrack marks which may indicate a bias in either (or indeed both) types of observation. Figure 4.11 shows that the total mean error for simulations measured against wrack marks tends to be roughly 0.25 m higher than the corresponding error for water marks – suggesting that water marks may be, on average, 0.25 m higher than wrack marks.



Figure 4.10. A water mark and a wrack mark deposited on a tree trunk by a flood in Tewkesbury, UK, May 2012. The water mark appears to exceed the wrack mark by some 5 cm, this could be due to capillary action of the tree bark. The top of the line of debris is approximately 15 cm above the water. Photo taken 3rd May 2012.

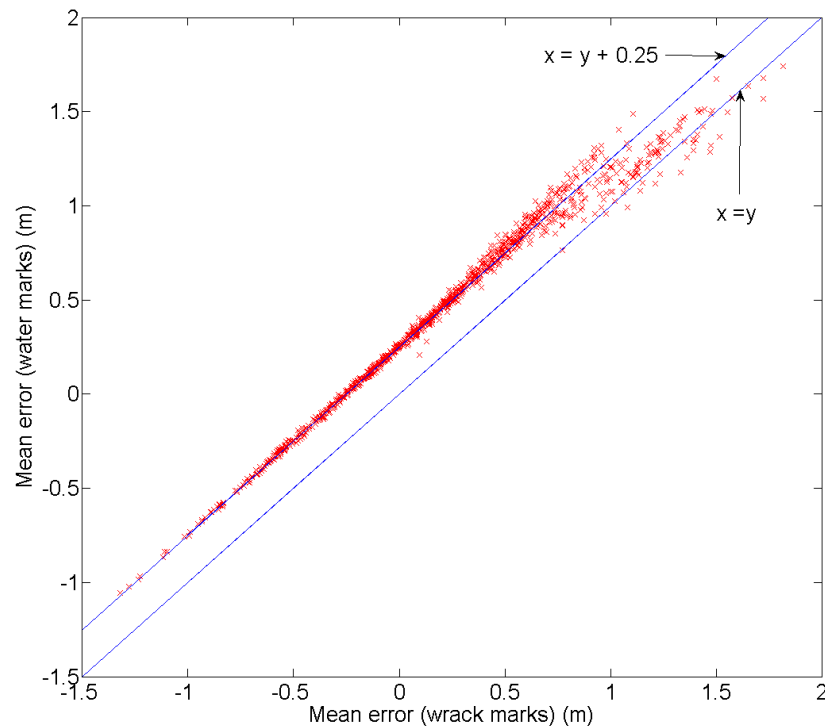


Figure 4.11. Mean error for all 999 model simulations measured using wrack mark observations (abscissa) and water mark observations (ordinate).

The numerical dominance of wrack marks (217) over water marks (43) might suggest that the bias between the two types of observation would be hidden by the smoothing algorithm, and this might well be the case if the water marks were geographically interspersed amongst the wrack marks. However, as can be seen from figure 4.2 the water marks are almost all located in the urban areas south of the Eden, with a particularly dense cluster west of the Petteril. This close geographical cluster in particular suggests that a systematic difference would not be hidden by the smoothing algorithm, and this can be seen in figure 4.12 where the difference in maximum water height is shown for the best performing simulation against both raw and smoothed observational data.

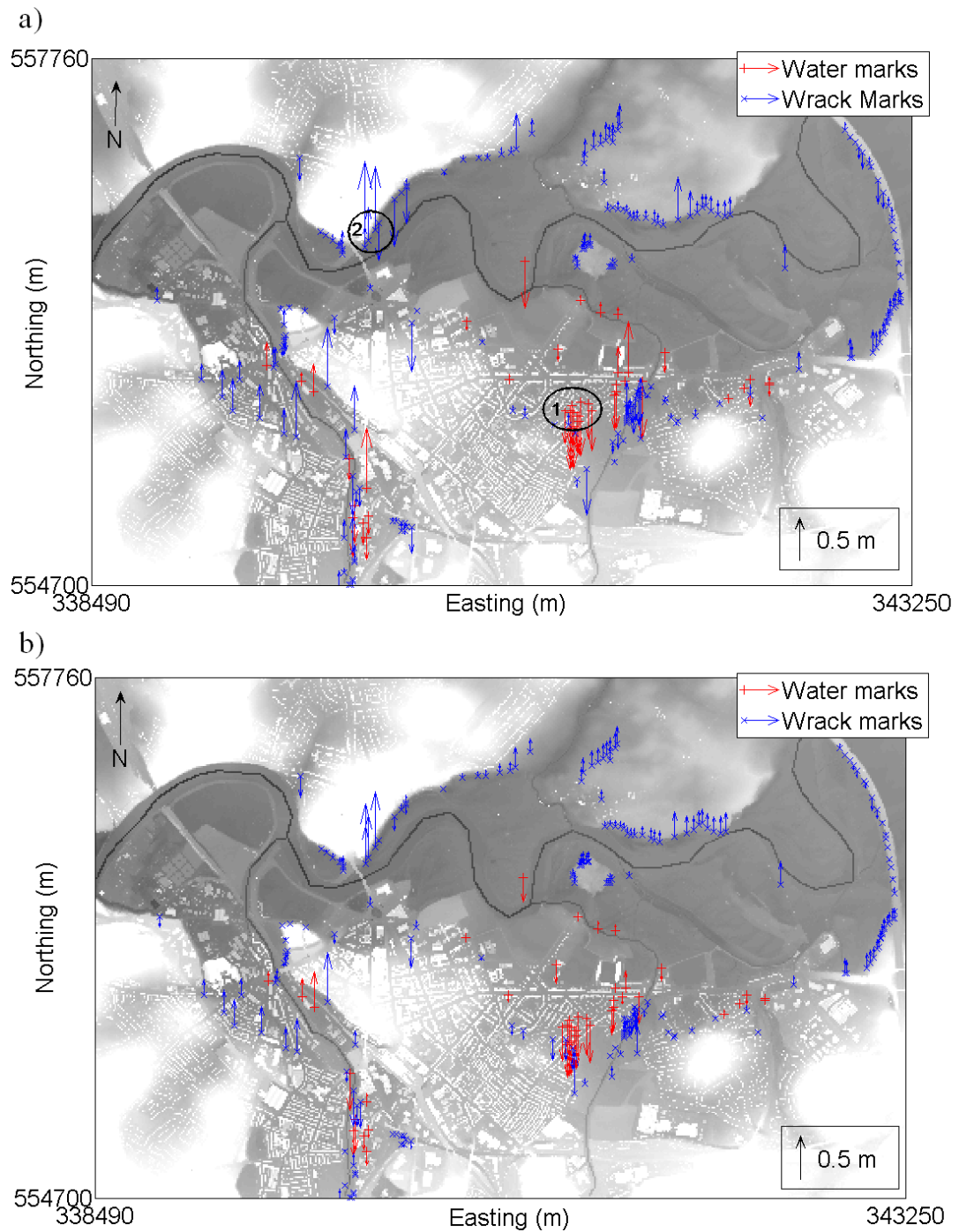


Figure 4.12. DEM of Carlisle showing how the best performing simulation compares against wrack (x) and water mark (+) observations. Up arrows indicate the simulation water depth exceeds the observation. (a) using raw observational data, (b) smoothed observational data. Highlighted in (a) is 1: the cluster of water marks to the West of the Petteril (discussed in section 4.4.4) and 2: the watermarks upstream of the A7 bridge (discussed in section 4.4.5).

Figure 4.12 shows that many of the isolated larger errors are considerably reduced by the smoothing process, but where the errors are clustered together they largely remain intact. For example the cluster of water marks to the west of the Petteril (see highlighted area 1 in figure 12a) which is observed to be above the simulated water level and the nearby wrack marks, are not significantly reduced. Indeed, it is this cluster of points that account for most of the apparent bias between the wrack and water marks. No obvious reason for this cluster of 'raised' watermarks presents itself, but many factors may have contributed:

- The water marks are located in a densely urban area where there may be localized hydraulic effects not represented by the simulation.
- As reported by the Environment Agency (2005) there were reports of multiple debris blockages on the nearby River Petteril which can cause significant variation in water height over small distances.
- The flooding near the Petteril seemed to have been caused by the high discharge from the Petteril itself, but also from backwatering effects from the Eden when the main flood wave arrived. As figure 4.3 shows the timing of peak discharge on the Petteril and Caldew preceded the peak discharge on the Eden by some 10-12 hours, it could be that we are attempting to compare marks of maximum water levels deposited at different times.
- The observed water marks are measured to be higher than most nearby observations. It could be that the flood water depth was locally increased from upsurge from a drainage system.
- Finally, it is likely that there are errors in identifying and recording the location of the marks, as previously discussed.

#### 4.4.5 Localised hydraulic effects

Figure 4.12 (b) shows how the differences between simulated water heights and observations of wrack marks located in rural areas to the north and east of the study area are noticeably reduced by the correction algorithm. This suggests that the smoothing algorithm may provide the most benefit in rural areas where there are densely populated series of homogenous measurement types unaffected by the complicating factors of urban flooding. The notable exceptions are the four



observations immediately to the east of the large bridge over the River Eden (see highlighted area 2 in figure 4.12a). These four observations are well below both the observations immediately upstream and the simulated water level at this point (see figure 4.13).

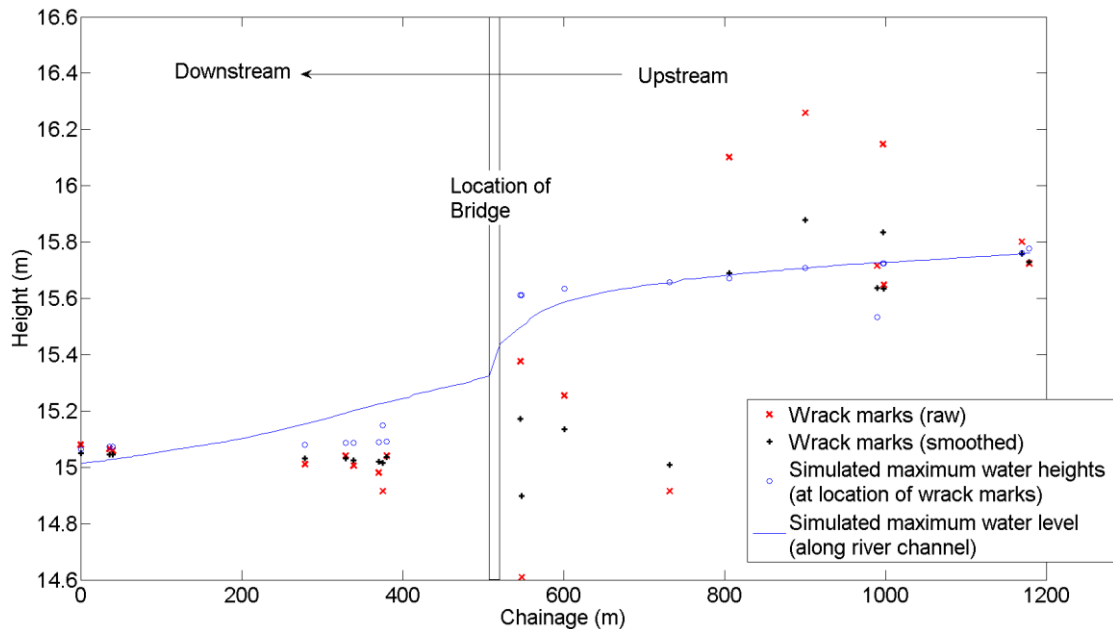


Figure 4.13. Height of uncorrected (x) and smoothed (+) wrack mark observations near the A7 bridge on the River Eden plotted against river chainage. Also shown are the simulated maximum water levels from the best performing simulation.

Figure 4.13 clearly shows the effect of the bridge on the simulated water levels. It can be seen that the observations downstream are consistent with each other and the simulation. However this is not the case for the observations immediately upstream of the bridge. There seems to be considerable error present in some of the observations upstream from the bridge where recorded water levels between adjacent observations differ by up to 1.1 m. Although the smoothing algorithm appears to bring some of the observations closer to the simulated levels, it did not improve the 4 observations immediately upstream from the bridge.

From a physical perspective the expected hydraulic effect of the bridge should be to reduce maximum water level moving from upstream to downstream due to the narrowing of the channel (as the simulated water level shows), but this effect would not be manifest in the smoothing algorithm. Instead the algorithm would use the

observations downstream of the bridge to adjust the upstream points downwards. Since the smoothing algorithm is removing information from the observational dataset, there are likely to be particular contexts where the effect will be to reduce, rather than increase, the accuracy of the measurements. This appears to be happening for at least two of the observations above the bridge, but the rather high inconsistency between neighbouring observations near the bridge makes it hard to isolate or quantify a negative effect. No obvious reason for the inconsistency in the observations above the bridge presents itself; the observations are located on a sloping bank sparsely populated with trees and shrubs so it could be that the slope of the bank and the vegetation made it difficult to identify the wrack marks correctly. Alternatively the presence of the bridge itself could be the cause by slowing down the dewatering process upstream such that debris was more likely to have been deposited by the descending flood water below the maximum water level. By ascertaining that, for these particular readings, the smoothing algorithm appears to have little or no beneficial effect it may be decided, after consideration of the characteristics and location of these readings, that the value of the dataset is improved by discounting these readings entirely.

#### 4.4.6 Possible impact on model uncertainty

A lot of the analysis in sections 4.4.3 and 4.4.4 has focused on the single, best performing model simulation as scored using the RMSE of all observations. However, it has long been recognised that the uncertainties inherent in environmental modelling mean there are likely to be a number of parameter sets equally acceptable in simulating the observed behaviour (Beven, 2006), a concept now known as equifinality (Beven and Freer, 2001). The generalised likelihood uncertainty estimation (GLUE) technique proposed by Beven and Binley (1992) is a widely used method for identifying the acceptable subset of the parameter space (Beven, 2006). Aronica et al. (2002) extended the GLUE technique by proposing a way of weighting model parameter sets based on the ability of the simulations to match flood extent data, then producing 2-D probability maps to give spatially distributed estimates of uncertainty. These probabilistic flood maps are a powerful way of visualising the uncertainty in the predictive precision of flood models. Here we establish the likely effect the smoothing

algorithm would have on probabilistic flood maps produced as a result of the simulations performed in this study.

Beven (2006) points out that the choice of weighting scheme and the decision of whether a parameter set is considered behavioural is often subjective. It is also intrinsically linked to the uncertainty in the observational datasets (Schumann et al., 2007b), so if the proposed smoothing algorithm does indeed reduce the uncertainty in the observational dataset it may also impact which model parameter sets are considered behavioural. To establish if this is the case, we took an approach commented on by Refsgaard et al. (2006) which is to compare the RMSE of the simulation with the observational uncertainty. In this case, if the model is to have skill at predicting inundation depths for future flood events in the domain, the uncertainty in the DEM must also be considered and combined with the observational uncertainty of the wrack and water mark readings. Mason et al. (2007b) estimate the RMSE of the DEM ( $U_{DEM}$ ) to be 0.18 m. In section 4.3.1 we compared wrack and water mark height readings with near neighbours to give an estimate of observational uncertainty ( $U_{obs}$ ) of 0.105 m for the raw readings which is reduced to 0.038 m by the smoothing algorithm. Since these errors are statistically independent, the total observational uncertainty ( $U$ ) is given by the root sum square:

$$U = \sqrt{U_{DEM}^2 + U_{obs}^2} \quad (4.3)$$

Equation 4.3 gives values for  $U$  of 0.206 m using the raw readings and 0.184 m for the smoothed readings. Scoring the parameter sets of the 999 model runs in the Monte Carlo simulation and rejecting those where the RMSE is greater than twice the uncertainty results in a smaller number of parameter sets considered behavioural (235) when using the smoothed data than the raw data (267). The possibility, shown by these results, of using the smoothing algorithm to narrow the selection of behavioural parameter sets demonstrates its potential value in increasing the precision of predictions from flood models.

#### 4.5. Discussion and conclusions

This paper has examined the accuracy of a set of point observations of high water marks left after a severe flood in Carlisle, UK in January 2005. Whilst it is clear there are errors in the observations, the lack of reference data makes it difficult to quantify and identify the inaccuracies. A smoothing algorithm is described that highlights the most inconsistent observations and can be applied to the dataset to reduce the inconsistency between observations and their near neighbours. The efficacy of the smoothing algorithm is evaluated by comparing the 'raw' and 'corrected' measurements against the peak water level recorded by two river gauges in the study area, and the results suggest the correction algorithm is broadly successful at reducing the error in the observational dataset. The algorithm was assessed through the use of a set of Monte Carlo simulations of a hydraulic model of the event showing how the smoothing algorithm can lead to improvements in model predictions by reducing model uncertainty. Furthermore two areas were highlighted that showed distinct local inconsistency which would not be removed by applying the smoothing algorithm, providing the additional benefit of better informing the researcher to make the necessary subjective inferences on the data. Ideally flood modellers would not need to introduce such subjectivity, however, in reality, the limitations of the models and data often necessitate it as discussed by Pappenberger et al. (2007b) and Schumann et al. (2009).

Whilst we accept that if the smoothing algorithm is applied without due consideration of the characteristics of the particular study event there is the possibility that it may reduce the overall information content in the dataset. However, given the inherent scarcity of, and unavoidable uncertainty in observational data of extreme floods, any technique that either improves data quality or, at minimum, assists in highlighting and quantifying errors is potentially of great benefit to researchers. Furthermore, the spread of GPS enabled camera phones and other consumer devices is enabling the collation of point observations from the public (see for example Met Office, 2012; Parkin, 2010). The resulting datasets are likely to be prone to stochastic uncertainty thus increasing the necessity of data cleansing techniques such as the smoothing algorithm described here. Further examination of the method in other case

studies would be welcomed especially where extensive validation from an alternative source such as aerial photos or SAR images is available.

### **Influence on water resources infrastructure and managing risks**

This paper highlights the hydraulic complexity of modelling floods in built-up, high risk areas where the hazard of flooding is greatest. The difficulties don't just arise from the need to run simulations at a high enough resolution to reflect the small scale hydraulic effects caused by buildings, bridges and existing flood mitigation infrastructure. Other factors to consider include: the practice of using a single, global figure for the floodplain roughness, whereas concreted urban areas would have a very low friction in contrast to areas under vegetation and these differences are not adequately represented by a global friction parameter; sub-surface features such as culverts and drains that may not be included in the model will affect localized water levels; remote sensed observations of water extent, or indeed in situ observations can be impeded by tall structures (Horritt et al., 2010; Schumann et al., 2011); the relative abundance of bridges and artificial channel constraint in urban areas means channel blockages are more likely to occur during a flood, this will influence the dynamics of the flood but is currently beyond the scope of most hydraulic modelling codes. In the case of the 2005 Carlisle flood it is likely that some combination of these factors is the reason the model uncertainty is higher in the urban than the rural areas. From the perspective of water resource infrastructure planning and flood risk management it is certainly a priority to reduce uncertainty in high risk areas by continuing the recent advances in monitoring, understanding and simulating urban flooding.

## Chapter 5. Flood model structure and calibration

### 5.1 Introduction

This chapter details the process and results of modelling the January 2005 Carlisle flood that was described in chapter 2. The hydraulic flood model has already been introduced in chapter 4; in this chapter further detail is provided including sensitivity analysis and alternative methods of calibration supporting the use of the calibrated model's parameter sets in estimating the uncertainty in design floods performed in chapter 8.

First in section 5.2 a basic 1-D modelling exercise is described, the results of which are then used for calibrating the full 1-D/2-D LISFLOOD-FP simulations described in section 5.3. The sensitivity of the model to parameter variation is examined in section 5.4 prior to calibrating the model under the GLUE methodology of Beven and Binley (1992) from which a probabilistic flood map of the event can be generated (section 5.6) to take account of model parameter and observational uncertainty. A global measure of model performance, giving equal weight to all observations of flood depth and extent, is then compared against a range of alternative, subjective evaluation schemes that can lead to a continuum of risk based probabilistic flood maps (section 5.7). Finally, in section 5.8, the results of a risk-based calibration scheme using only observations in urban areas are compared with the results of the global calibration scheme.

### 5.2 Basic 1D modelling

Chapter 3 provided background on the history of computational flood modelling and described how the history of flood modelling has seen an evolution from simpler 1-D models facilitated by the availability of ever more powerful computers. However some sophisticated modern models like ISIS 1D (ISIS, 2014b) still describe themselves as one dimensional, and often relatively simple methods involving 1D interpolations of the water slope are used to evaluate the results of more complex models (for example see Horritt and Bates, 2001b; Mason et al., 2009; Stephens et al., 2012). Schuman et al. (2007b) and Di Baldassarre et al. (2010) implement a simple planar 1D model based on

a linear interpolation of measured water levels at the start and end of the reach to define the upper limit placed on the 2D simulation results. The approach taken here is very similar: a simple 1-D interpolation model of the flood is defined and evaluated against the observational data from the event. The performance of the 1-D model is then used as the limit of acceptability for the evaluations of the 2-D model simulations performed subsequently. I.e. any 2-D simulations that do not perform better than the simple 1D simulation are rejected as not providing any value to the modeller.

The simple 1-D linear slope model uses maximum water surface elevations upstream and downstream from river gauge readings and assumes a uniform water slope between the upstream and downstream points. All areas of the DEM which are below the water level at the channel are assumed inundated. This is similar to the 'linear interpolation' model described by Apel et al (2009a). Both the simple 1-D mode and the LISFLOOD-FP 1-D/2-D model cover precisely the same model domain (see figure 5.1).

The resulting 1-D model has four parameters: the maximum water level of the River Eden upstream (where it enters the model domain) and downstream (where it leaves the model domain) and the maximum upstream water level of the Rivers Caldew and Petteril where they enter the model domain (see figure 2.8). The slopes of the Rivers Caldew and Petteril were constrained such that the downstream water height matches the water height of the River Eden and their respective confluences. The model was calibrated by generating a uniform Latin Hypercube Sample (ULHS) (see Saltelli et al., 2000) of 999 parameter sets varying all four model parameters. In order to define physically realistic ranges for the parameters, maximum water levels at the upstream (entry) and downstream (exit) points for the rivers to the model domain were estimated from the nearest river gauge data, and the parameters in the ULHS varied in a range encompassing those estimated values. See table 5.1 for the ranges of the parameters.

The observational dataset described in section 2.6.2 was used to evaluate the results of the 999 simulations of the simple 1-D model. The difference, or error, between the observation elevation and the simulated water level at the point of the

channel that is geographically closest (i.e. straight line distance) to the point of observation were calculated and the root mean square error (RMSE) was used to score each simulation. The lowest RMSE was 0.411 m; the extent and distribution of the differences between the observed and simulated water levels are shown in figure 5.1.

Table 5.1. Parameter ranges in ULHS for simple 1-D model.

Parameter	Coordinates (BNG)		Range of water height (mAOD)	Parameter values of best performing simulation (mAOD)
	Easting	Northing		
<b>Eden Upstream</b>	342,688	557,502	16 - 17	16.798
<b>Eden Downstream</b>	338,489	556,580	13.5 – 14.5	14.144
<b>Caldew Upstream</b>	339,958	554,717	16.5 – 18.5	17.237
<b>Petteril Upstream</b>	341,394	554,711	16 - 18	16.827

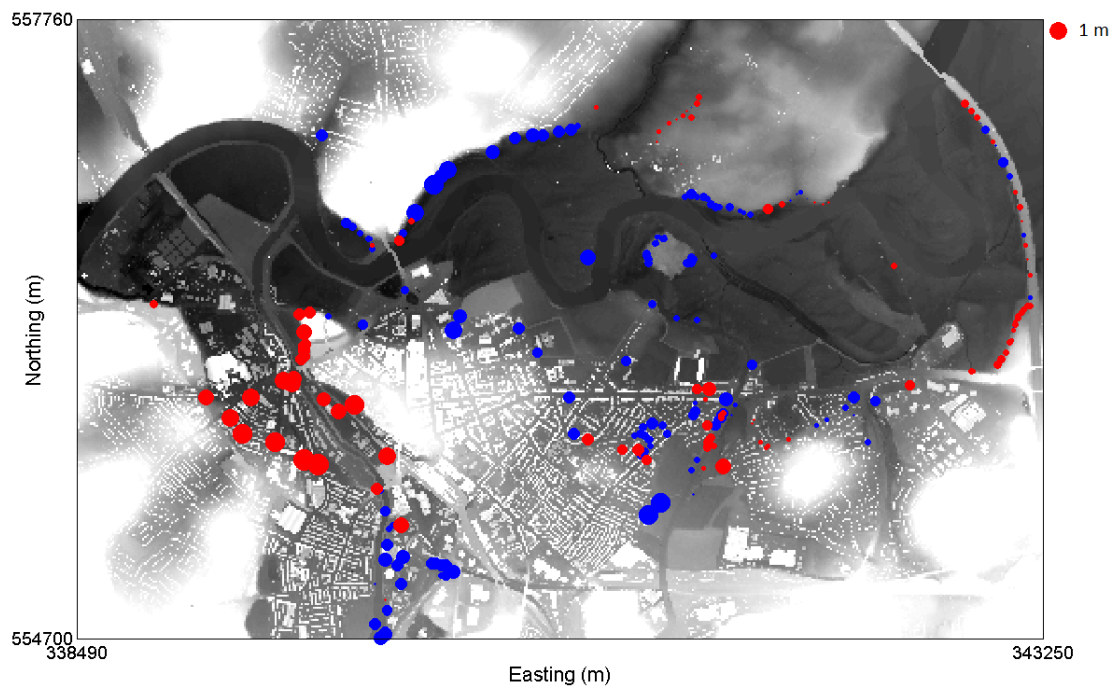


Figure 5.1. DEM of Carlisle showing how the best performing simple 1-D simulation compares against the observations of maximum water extent. Red circles indicate the simulated water depth exceeds the observation; blue circles indicate simulated water depths lower than the observation. Circles centred at the locations of observations and circle diameter indicates the relative magnitude of those differences between simulated and observed.



As can be seen from the results of the more detailed 1-D/2-D modelling in section 5.4, the simple 1-D model performs comparatively poorly; in this case it seems the topography and the complexity of 3 separate flood waves in 3 watercourses mean that a simple interpolation of water surface elevations provides an inadequate representation of the event. The RMSE of the best performing 1-D simulation (0.411 m) is used to define the upper limit for the RMSE of the 1-D/2-D simulations considered behavioural.

### 5.3 LISFLOOD-FP 1D/2D modelling results

The LISFLOOD-FP model configured as described in section 2.10 and a Monte Carlo simulation (Robert and Casella, 2004) of the January 2005 flood event was performed. Often when calibrating a 2-D hydraulic flood model, only 2 parameters are varied: the channel friction (Manning's  $n_{ch}$ ) and the floodplain friction (Manning's  $n_{fp}$ ) since these are the two main 'effective' parameters (see for example Fewtrell et al., 2008; Fewtrell et al., 2011a; Horritt and Bates, 2002; Neal et al., 2009; Stephens et al., 2012; Yu and Lane, 2006a), i.e. parameters that don't necessarily have a physically meaningful value and are used to compensate within the model for much of the necessary simplification of the physical processes (Beven, 2008). However in this case, as documented in section 2.7, it is likely that there is considerable uncertainty in the Eden, Caldew and Petteril hydrographs used as boundary conditions for the model. To account for that uncertainty, model parameters were introduced to vary the hydrographs for the Rivers Eden, Caldew and Petteril.

#### 5.3.1 Parameter variation of hydrographs

A discharge multiplier was applied to the discharge for each of the three rivers. The discharge multiplier is a factor (varied between 0.5 and 1.5) that was applied to all recorded/estimated discharge values above for the three rivers above a certain base flow level (see figure 2.9 for the unaltered hydrographs). In this way, the shapes and durations of the peaks of the hydrographs are unaltered, but the peaks are lowered or raised when a discharge multiplier is applied with a value of less than 1 or more than 1 respectively. The purpose of this hydrograph manipulation is to account for any potential bias in any of the river gauges that would systematically over- or under-

estimate the discharge. The modified discharge ( $Q_{mod}$ ) is calculated from the estimated (or measured) discharge ( $Q_{est}$ ) thus:

$$Q_{mod} = ((Q_{est} - Q_{base}) * Dm) + Q_{base} \quad (5.1)$$

Where  $Q_{base}$  is the base flow for the river and  $Dm$  the discharge multiplier to be applied.  $Q_{base}$  for each of the three rivers does not have any particular hydrological significance; it allows the magnitude of the simulated peak flow to be varied without changing the flow before and after the flood event. For example, the estimated discharge of the River Eden into the model domain was  $867.1 \text{ m}^3\text{s}^{-1}$  at 06:00 on 6 Jan 2005. To apply a discharge multiplier of 0.8 to this and using  $200 \text{ m}^3\text{s}^{-1}$  as the base flow gives a modified discharge ( $Q_{mod}$ ) of  $733.7 \text{ m}^3\text{s}^{-1}$ .

### 5.3.2 Monte Carlo Simulation

Details are given below of the 5 model parameters varied using a Latin Hypercube Sampling (LHS) method (Saltelli, 2008) to generate the 999 parameter sets. Each parameter is varied using uniform steps between minimum and maximum values deemed to be the feasible limits. In this way the sampling can be termed Uniform Latin Hypercube Sampling (ULHS).

1. Channel Roughness (Manning's  $n$ ) – single global value across the whole model domain, varied between  $0.03 \text{ m}^{1/3}\text{s}^{-1}$  and  $0.09 \text{ m}^{1/3}\text{s}^{-1}$
2. Floodplain Roughness (Manning's  $n$ ) – single global value across the whole model domain, varied between  $0.03 \text{ m}^{1/3}\text{s}^{-1}$  and  $0.09 \text{ m}^{1/3}\text{s}^{-1}$ .
3. Eden discharge multiplier. A multiplier was applied to all upstream Eden discharge values above a certain base flow level ( $200 \text{ m}^3\text{s}^{-1}$ ). The portion of the discharge above the minimum was multiplied by the discharge multiplier. Discharge multiplier was varied between 0.5 and 1.5.
4. Caldew discharge multiplier. A multiplier applied to discharge on the Caldew above a base value ( $15 \text{ m}^3\text{s}^{-1}$ ). Discharge multiplier was varied between 0.5 and 1.5.
5. Petteril discharge multiplier. A multiplier applied to discharge on the Petteril above a base value ( $10 \text{ m}^3\text{s}^{-1}$ ). Discharge multiplier was varied between 0.5 and 1.5.

As discussed in section 5.3 the role of the Manning's  $n$  roughness parameters is partly as effective parameters, but in this case they also have a physical basis. Consequently the range of values for the 2 Manning's  $n$  parameters were selected to encompass all values deemed realistic for the types of channels and floodplain land cover in the study area. Specifically, the river channels in Carlisle are not straight and clear of obstructions; neither are they excessively weedy, especially in midwinter when the flood occurred. Away from the urban areas, the floodplains are largely grassland. Using a table of typical Manning's  $n$  provided by FSL (2006), a range of  $0.03 \text{ m}^{1/3}\text{s}^{-1}$  to  $0.09 \text{ m}^{1/3}\text{s}^{-1}$  was deemed wide enough to cover all realistic values for both the channel and floodplain Manning's  $n$ .

### 5.3.3 Model Performance Scoring

The maximum water extent from each simulation was then compared to the water extent as recorded by the observations of wrack and water marks (section 2.6.2). Model errors for each observation location are calculated as the difference between the heights of the observations and the maximum simulated water levels at the locations of the observations. If the simulated water extent does not reach the location of the wrack or water mark, the nearby model cells were systematically searched to identify the nearest inundated cell, and the water level taken from that cell.

Although the main measure of model performance used here is the root mean square error (RMSE) of the simulations, it is also sensible to examine the mean error. This can give an indication of potential bias in the simulations to over- or under-predict water levels. The relationship between mean error and RMSE for the 999 Monte Carlo simulations (figure 5.2) shows a particular correlation where both the magnitude of the mean error and RMSE are large. This is to be expected, as there is likely to be an asymptotically linear relationship between mean error and RMSE: simulations that strongly over-(under-)predict the water level across the whole study area will show a strongly positive (negative) mean error and correspondingly high RMSE. The values for mean error extend further to the positive than negative. However this, in itself does not suggest a bias to over-prediction of simulated water levels; the likely reason is

simply that no simulation can give a mean under-prediction of more than approximately 1.5 m because that is equivalent to no flooding.

Figure 5.2b shows more detail for the simulations that score well for both mean error and RMSE; here there is no clear relationship between the two measures of model performance, when considering only the 266 model simulations considered behavioural (RMSE less than 0.411 m), approximately half (134) give a mean error of less than zero. This strongly suggests there is no significant bias towards over- or under- predicting the flood extent. Consequently RMSE is primarily used for model evaluation.

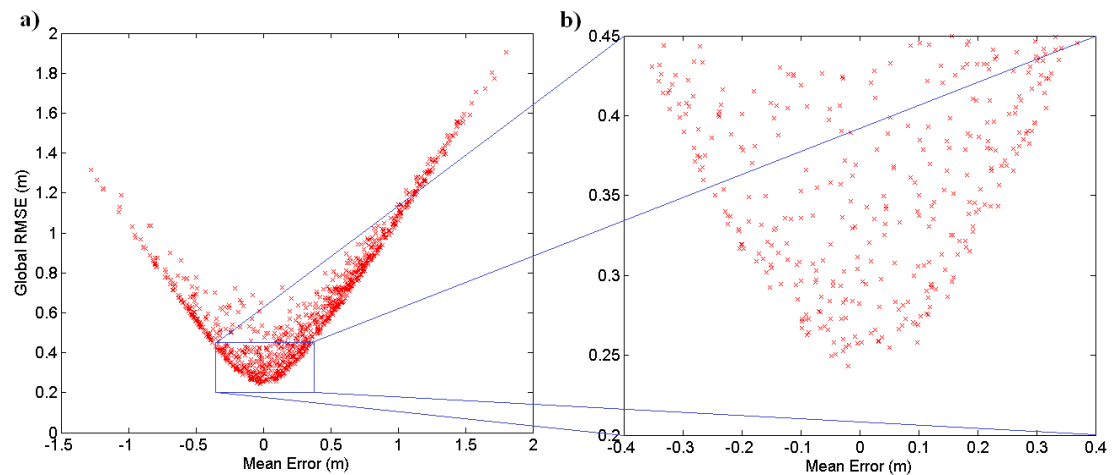


Figure 5.2. Mean error and RMSE scores for the 999 Monte Carlo simulations. a) all simulation results, b) cropped to show only simulations with an RMSE less than 0.45 m.

#### 5.4 Sensitivity Analysis

The global RMSE of all 999 runs from the Monte Carlo Simulation were calculated, and the best performing simulation under this measure gave an RMSE of 0.243 m. However, under the principle of model equifinality discussed in section 3.5, the identification of a single model parameter set is a misleading representation of the natural process being simulated where the parameters have little or no physical meaning (Beven, 2006). Not only must approximations in model parameters, structure and boundary conditions be accounted for, but also the uncertainty and incommensurability of the observational data as discussed in chapter 4.

A sensitivity analysis was performed on the simulation results in order to gain an understanding of the effect on model performance of individual model parameters.

As a first step, scatter plots showing how the RMSE score of each simulation varies against individual model parameters were produced. A visual inspection of the 'shape' or 'pattern' of the scatter plots (Saltelli, 2008 p.14) gives a suggestion of which parameters have the most effect on model performance. Scatter plots of the results of the simulations can be seen in figure 5.3.

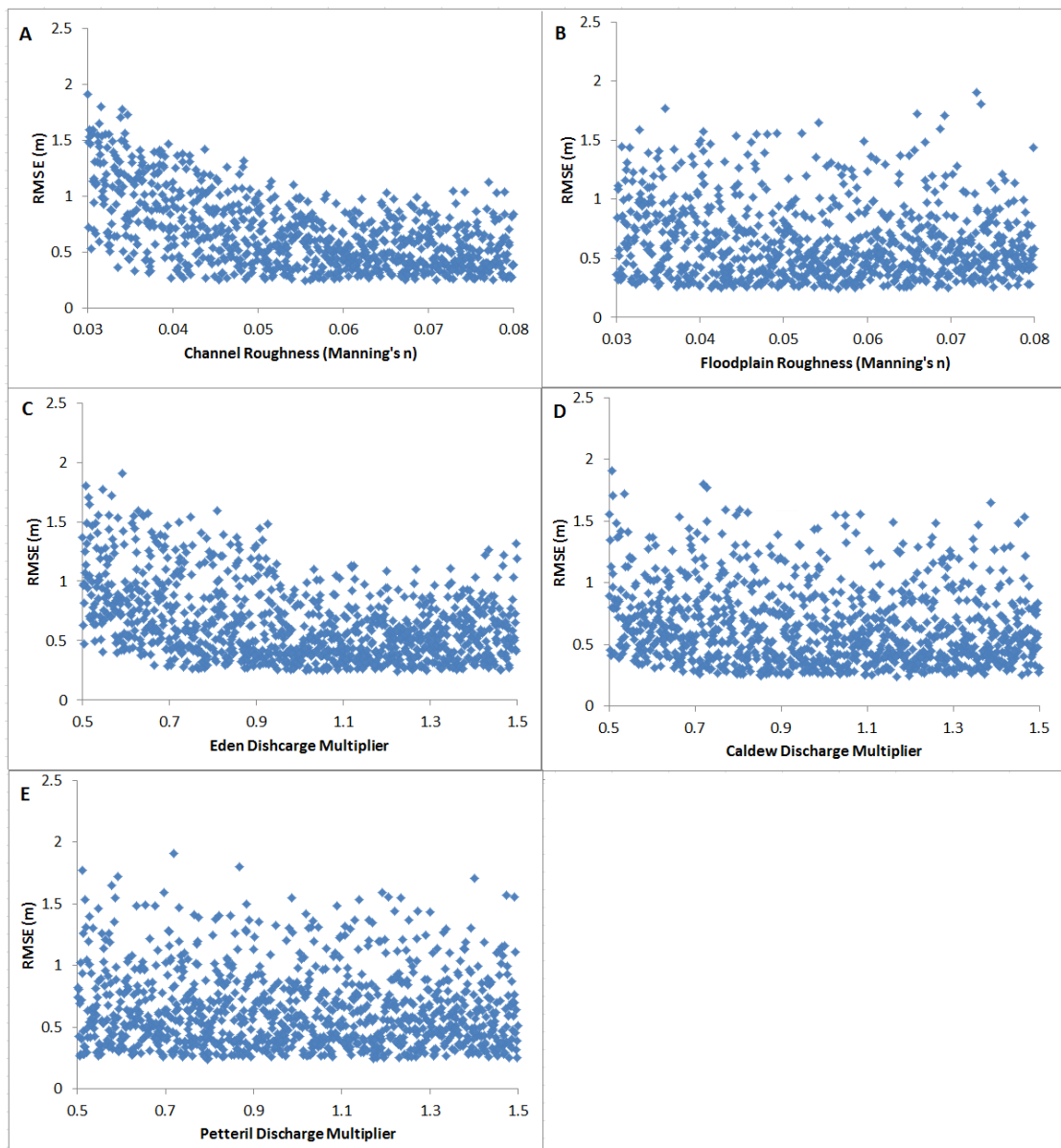


Figure 5.3. Scatter plots of root mean square error (RMSE) against the 5 model parameters varied for the Latin Hypercube sampling (999 simulations).

The pattern evident in figure 5.3a indicated the model is most sensitive to the channel roughness parameter. Of the 3 parameters where the discharges of the watercourses are varied (figure 5.3 c,d,e), it is unsurprising that the model is most sensitive to the discharge in the largest river: the Eden.

The sample of 999 simulation results can be used to estimate the first order sensitivity of the model to the 5 parameters that were varied. Using the method of Sobol' (Saltelli et al., 2000 p.174), the main effect or first order sensitivity  $S_i$  of a model to a parameter  $X_i$  is given by

$$S_i = V_i / V \quad (5.2)$$

Where  $V$  is the total variance of the results and  $V_i$  is the variance due to the parameter  $X_i$  (Clope et al., 2008).  $V_i$  was calculated for the 5 parameters varied in the sample using the method described in Saltelli et al. (2008 p.21) whereby the simulation results are sliced up according to the values of the input parameters, and the output variance is calculated for each slice. In this case, each parameter was divided into 10 equal slices, and since the Latin Hypercube sampling used a uniform sampling strategy for the parameters, each slice would contain 100 simulations (one slice would contain 99 simulations). The variance of each slice was calculated and the mean of the variances was taken for the 5 parameters. The result is an approximation of the portion of the total variance that is not caused by the specific parameter ( $V_{\sim i}$ ), such that

$$V = V_{\sim i} + V_i \quad (5.3)$$

Allowing  $V_i$  and hence  $S_i$  to be calculated from equation 5.3. The results are shown in Table 5.2. The results in table 5.2 confirm the suggestion from the scatter plots that the model has the highest first order sensitivity to the channel roughness parameter. The higher sensitivity of the model to the Eden discharge compared to the Caldew and Petteril discharges is not unexpected because the discharge on the Eden is so much greater than the other rivers.

Table 5.2. Sensitivity indices of the model to the 5 parameters varied on the Latin Hypercube sample

<b>Parameter (<math>X_i</math>)</b>	<b>First order sensitivity index (<math>S_i</math>)</b>
<b>Channel roughness</b>	0.343
<b>Floodplain roughness</b>	0.025
<b>Eden discharge multiplier</b>	0.201
<b>Caldew discharge multiplier</b>	0.036
<b>Petteril discharge multiplier</b>	0.000
<b>Total first order sensitivity</b>	0.605

The RMSE value is a single global score and the relative discharge from the Caldew and Petteril compared to the Eden (figure 2.9) means the discharge values of the smaller rivers are likely to have a significant effect only on the wrack and water marks in their localities. However, at this point a global measure of model performance is being used, where equal weight is given to all observations. Under alternative, subjective model evaluation schemes considering the vulnerability to the hazard, the relative sensitivity of the model to discharge on the smaller rivers may increase if, for example, the flooding from these sources tends to disproportionately affect urban areas. This effect is explored in section 5.7.

The lack of sensitivity of the model to the floodplain roughness parameter is worth discussing. When researchers first started developing 2D hydraulic models with 3D DEMs, their models tended to have a coarser resolution without the ability to resolve the finer details of the landscape, particularly in urban areas (see for example Horritt and Bates, 2001a; Werner et al., 2005). As a result the floodplain roughness parameter tended to serve as an effective parameter (Beven, 2008) that could compensate for some of the lack of detail in the landscape. This issue is discussed for the same study event by Neal et al. (2009) who modelled the same Carlisle flood event with a 25 m grid scale resolution, which is generally larger than many of the typical building footprints in the area. However, as model resolution increases, so the DEM becomes more representative of the physical topography reducing the influence of the single, floodplain roughness parameter.

Having examined the first order sensitivity to the model, the global RMSE simulation scores are used for model calibration allowing the creation of a probabilistic flood map of the event.

## 5.5 Global model calibration

The model calibration process continues by examining the response of the model as parameters are varied whilst keeping the other three parameters constant. Using these results, contour plots are a useful calibration tool for visualising the model response and identifying local maxima in the 2-D parameter space. Whilst it would no doubt be more useful to do this with the 5-D model space, it would be beyond the scope of this research to attempt to represent a 5-D visualisation in a 2-D medium. Notwithstanding this, the contour plots can provide beneficial insights into the characteristics of the model that can direct the subsequent steps in the calibration process.

In this section the results of two calibration exercises are presented: first the model performance was examined as the channel roughness and Eden discharge multiplier were varied, these being the 2 parameters with the highest first order sensitivity (see table 5.2); next the channel roughness and Caldew discharge multiplier were varied. Since the response to the Caldew discharge multiplier is localised to the geographical area around the Caldew, differences in the suggested optimal parameter configurations suggest it may be beneficial to use distributed rather than global roughness parameters.

### **Calibration varying channel roughness and Eden discharge multiplier**

200 simulations were run with the channel roughness varying between 0.04 and 0.85 (10 values) and the Eden discharge multiplier varying between 0.7 and 1.65 (20 values). The floodplain roughness and Caldew and Petteril discharge multipliers were held constant at 0.055, 1 and 1 respectively. The contour plot (Figure 5.4) showing how the RMSE varies with the 2 parameters has a clearly defined model optimum where the channel roughness is 0.065 and the Eden discharge multiplier is approximately 1.1, this indicates a simple interaction between these two parameters.



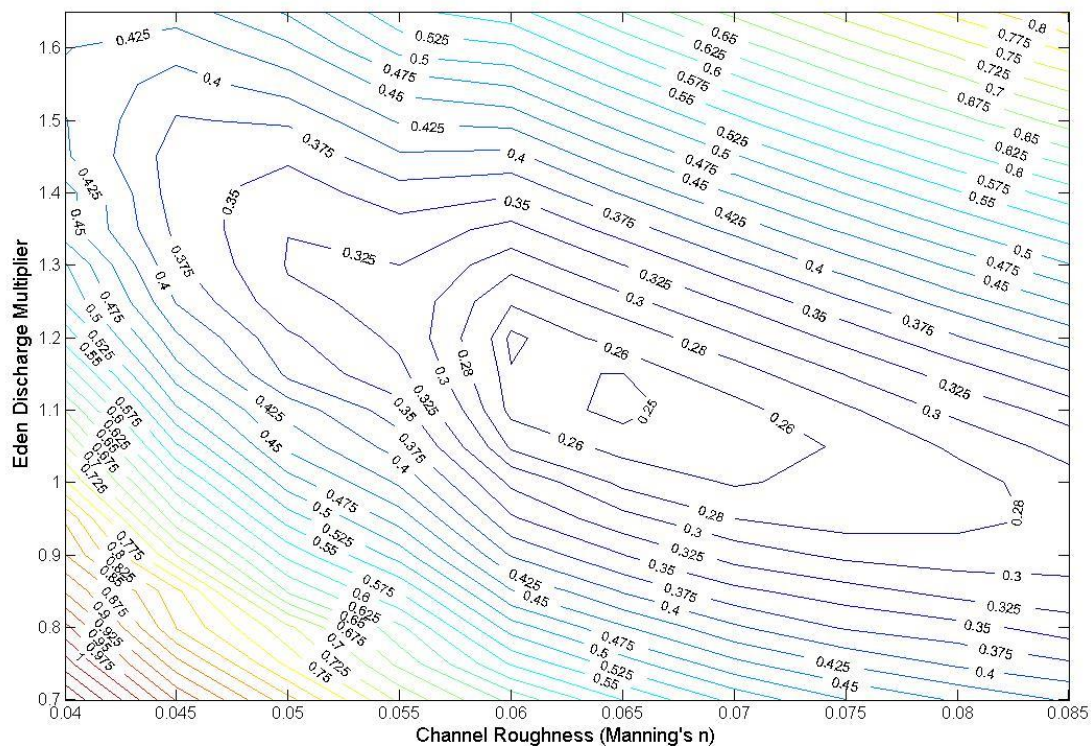


Figure 5.4. Contour map of RMSE (m) when varying Eden discharge multiplier and Channel roughness.

#### Calibration varying channel roughness and Caldew discharge multiplier

200 simulations were run with the channel roughness varying between 0.04 and 0.85 (10 values) and the Caldew discharge multiplier varying between 0.7 and 1.65 (20 values). The floodplain roughness and Eden and Petteril discharge multipliers were held constant at 0.055, 1 and 1 respectively. Figure 5.5 shows a contour plot of how the RMSE varies with the 2 parameters.

Whilst both contour plots (figures 5.4 and 5.5) show a broadly similar shape, the optimal parameter configurations are not completely consistent across the two calibration exercises. In particular, figure 5.5 shows that many behavioural simulations occur with a Caldew discharge multiplier of less than one and a high channel roughness, even beyond the value of 0.085 originally deemed the behavioural limit. Whilst this could suggest the models should be calibrated using distributed values of channel discharge such that the Caldew is given a higher channel roughness,

consideration of local witness accounts suggest another subtly different reason: there is anecdotal evidence of a build-up of debris under a bridge on the River Caldew (Environment Agency, 2005). This would have a similar effect to raising the effective channel roughness parameter, so a higher channel roughness for the Caldew channel than the Eden may produce more favourable model results but perhaps for the wrong reasons. If this model is to have value in improving the quantification of flood risk in Carlisle rather than merely replicating the 2005 event then it may be detrimental to increase the number of parameters and over-fit the model (Beven, 2006; Beven, 2008; Lee et al., 2012). It is a limitation of the model that the risk of full or partial stream blockage cannot be simulated so the decision was taken to accept the limitation rather than attempt to manipulate the parameters to better fit local observations. If more information were available as to the extent and location of any channel blockages then it may be possible to execute some model runs with simulated blockages to give a useful range of the likely outcomes for future events.

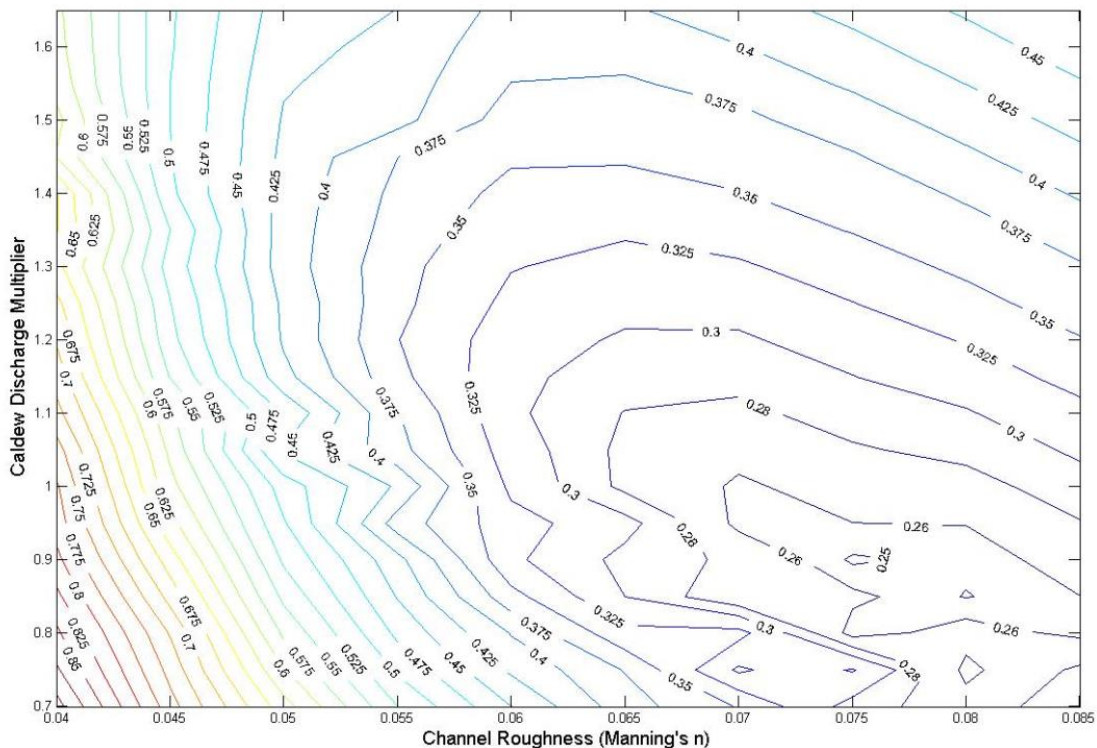


Figure 5.5. Contour map of RMSE (m) when varying Caldew discharge multiplier and Channel roughness.

## 5.6 GLUE uncertainty analysis

The debate between proponents of the GLUE methodology proposed by Beven and Binley (1992) and their critics such as Mantovan and Todini (2006), who favour more formal, probabilistic methods of uncertainty evaluation, looks set to continue (see section 3.5). In the case of evaluating a distributed hydraulic model, the data scarcity, the many degrees of freedom and possible inter-correlation between parameters and errors create considerable difficulties in defining formal distribution functions required for a probabilistic uncertainty analysis (Bates et al., 2014; Beven, 2006; Montanari et al., 2009). Furthermore, since each model simulation can take several hours to run, it is only feasible to run Monte Carlo simulations in a parallel computing environment making implementing Markov Chain strategies for exploring the parameter space difficult. Consequently the GLUE methodology was selected to analyse the uncertainty in the hydraulic model simulations of the Carlisle 2005 event and identify the model parameter sets that result in behavioural model simulations.

### 5.6.1 Behavioural simulations and likelihood function

Judgments about whether a given parameter set results in a behavioural simulation and what form the likelihood measure should take are necessarily subjective (Hunter et al., 2005a). Here the result of the RMSE of the best performing simple planar 1D simulation (0.411 m) is used as the upper limit for the RMSE of the 1D/2D hydraulic model simulations: i.e. any parameter sets resulting in simulations giving an RMSE of greater than 0.411 m are rejected as unbehavioural (similar to the approach used by Di Baldassarre et al., 2010; Schumann et al., 2007b). This upper limit for the 1D/2D model can be thought of as the point at which the model begins to show 'skill' beyond the simple planar 1D simulation (Horritt et al., 2007). In addition, Refsgaard et al. (2006) suggest using the uncertainty of observations as a reference for model performance. In chapter 4 the observational uncertainty was estimated to be 0.206 m, so all parameter sets resulting in simulations giving an RMSE within the observational uncertainty are given an equal (maximum) likelihood. Parameter sets resulting in RMSE scores between 0.206 and 0.411 m are given a likelihood score based on a straight line interpolation between the two thresholds. The resulting likelihood function just described is summarised below:

- All model realisations that give a global RMSE score worse than the simple 1-D interpolation ( $E_{max}$ ) (0.411 m) are rejected as not behavioural and given a likelihood of zero.
- All model realisations that give a global RMSE score within the estimated total observational uncertainty ( $U$ ) (0.206 m) are treated as equally credible and given a likelihood score of 1.
- Model realisations with a global RMSE score between 0.206 m and 0.411 m are given likelihood scores between 1 and 0 based on a linear interpolation.
- The likelihoods are then scaled such that the sum of all model realisation likelihoods totals to unity.

This gives a formula for calculating the likelihood ( $L$ ) for the  $i^{th}$  a model realisation of the Monte Carlo simulation as:

$$\begin{aligned}
 L(i) &= 0 && \text{for } RMSE(i) > E_{max} \\
 &= 1 - (RMSE(i) - U)/E_{max} && \text{for } U > RMSE(i) < E_{max} \\
 &= 1 && \text{for } RMSE(i) \leq U
 \end{aligned} \tag{5.4}$$

The likelihoods are then normalised ( $L_{norm}$ ) across all  $n$  behavioural simulations such that:

$$L_{norm}(i) = L(i) / \sum_{i=1}^n L(i) \tag{5.5}$$

The results of processing the 999 realisations from the Monte Carlo simulation (section 5.3.2) are discussed in the following section.

### 5.6.2 Results of the GLUE methodology

#### **Identifying Behavioural Realisations**

Once the results of the 999 Monte Carlo simulations are available, the next step is to reject all realisations considered un-behavioural. In this case, as discussed in section 5.6.1 above, any simulations with an RMSE greater than 0.411 m ( $E_{max}$ ) are rejected.

This screening leaves 266 of the original 999 realisations that are considered behavioural.

### **Applying likelihood to behavioural simulations**

Section 4.4.6 estimates the total observational uncertainty ( $U$ ) to be 0.206, so using equations 5.4 and 5.5, the likelihood ( $L$ ) and normalised likelihood ( $L_{\text{norm}}$ ) for all 266 behavioural realisations are calculated. The normalised likelihoods are combined to give a probability of inundation between 0 and 1 for each cell in the study area. Following a method described by Aronica et al. (2002), this makes a probabilistic flood map showing the spatial uncertainty of inundation for each cell in the study area. Figure 5.6 shows the probabilistic flood map for the January 2005 flood in Carlisle which shows the binary probability that an area will be flooded or remain dry, i.e. the extent of the flooding.

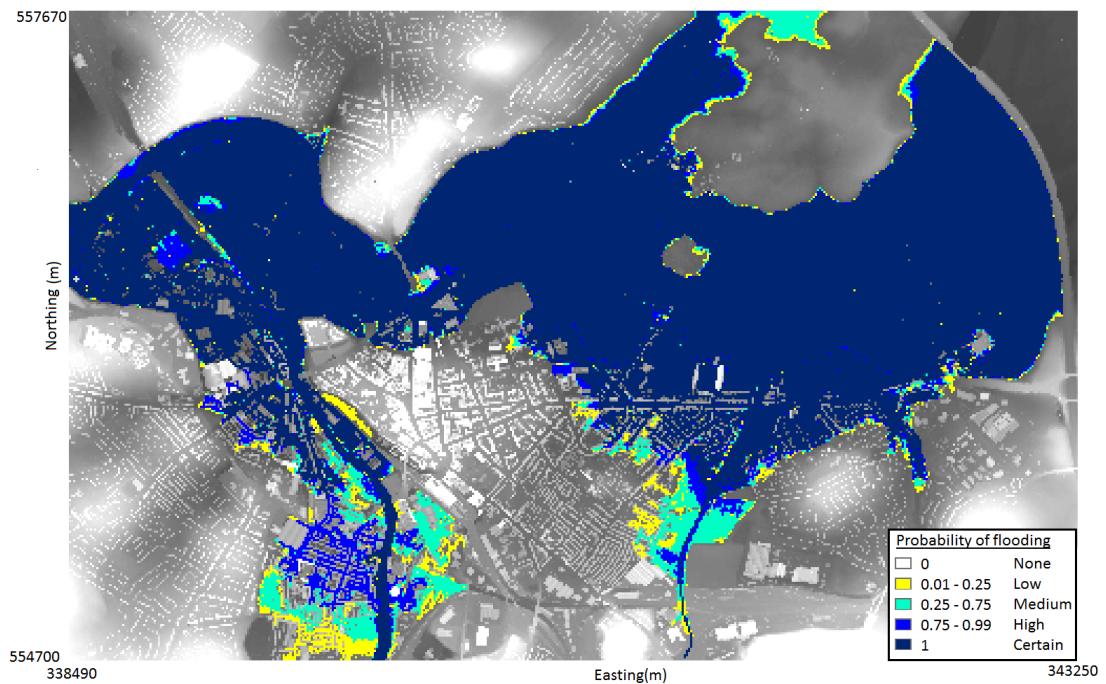


Figure 5.6. DEM for Carlisle overlaid by probabilistic flood map for the January 2005 flood. Pixel colour represents probability of inundation and is not an indication of flood depth.

At this stage no consideration is given to flood depth. The figure indicates that it is in the urban locations to the south of the study area, particularly near the Rivers

Caldew and Petteril, where there is the greatest uncertainty about the probability of inundation. These are the areas where it cannot be said with certainty that flooding will or will not occur given an event of similar magnitude to the January, 2005 flood. This result is unsurprising given the difficulties of urban flood modelling in general (section 3.3.2) and for Carlisle in particular (section 4.4.4).

### 5.7 Subjective model validation

The probabilistic flood map in figure 5.6 gives a graphic example of the sort of issue discussed by Pappenberger et al. (2007b): by scoring the model realisations using a global RMSE score that give equal weight to all observations, the researcher may be avoiding subjective choices based on the vulnerability of areas at flood risk. Indeed Pappenberger et al. (2007b) argue that the decision to give equal weight to observations in all locations is itself subjective. Ideally there would be additional flood data from the study area with which to validate the model calibrated on the January, 2005 event. But since extreme flood events are rare, the calibrated model is validated using several alternative model evaluation schemes sampled from the January, 2005 observational dataset (see section 2.6.2). Rather than use a random or some sort of systematic sampling method, sub-categories of the data are based on locality, observation type or vulnerability, and variations between the resulting probabilistic flood maps are examined.

Since the topography of the study area is relatively complex with three watercourses of varying sizes responsible for the flooding, examining the performance of the model using a subset of the observations may highlight localised inadequacies in the model that weren't evident under a global calibration scheme due to the abundance of observations elsewhere. In some ways this is similar to many cross-validation schemes (Kohavi, 1995; Wainwright and Mulligan, 2004), except that in this case, the data is purposefully sampled to maximise the information gained in the context of this particular study event. Furthermore a subjective evaluation of the possible benefits of the modelling exercise may suggest that a localised scoring system giving a risk-based calibration scheme could outweigh the benefits of a global calibration scheme if the uncertainty in the areas where the consequences of flooding

are greatest can be reduced even at the expense the overall uncertainty. This is examined in section 5.8.

The criteria for selecting different sub-sets of the observational data set of surveyed wrack and water marks are:

- **Sub-regions** of the study event (Eden, Caldew and Petteril sub-regions) similar to the regions used by Neal et al. (2009). By examining model uncertainty in smaller geographical areas, specifically the areas around the three main watercourses, it may be possible to highlight localised effects not captured by the model, such as possible blockages by debris and flooding from other sources.
- **Land use type** (urban or rural). This was based on a visual categorisation of the data points performed using GIS software showing the locations of the observations overlaid on an Ordnance Survey map of Carlisle. Since the consequences of the flood hazard are typically far greater in urban areas than on undeveloped floodplain such as agricultural land (Posthumus et al., 2009), this is where the vulnerability to flooding is greatest. Consequently, it may be beneficial to 'tune' the model to perform best in urban areas. However, as discussed in chapter 4, the observational data from urban locations tends to show far greater localised inconsistency
- **Observation type** (wrack mark or water mark). Comparisons of results scored according to the type of observation may highlight any difference in accuracy or systematic bias between the two observation types. See chapter 4 for analysis of the differences between the two types of observation.

Figure 5.7 shows how these categorisations of observations are defined over the study area; further details are listed in table 5.3.



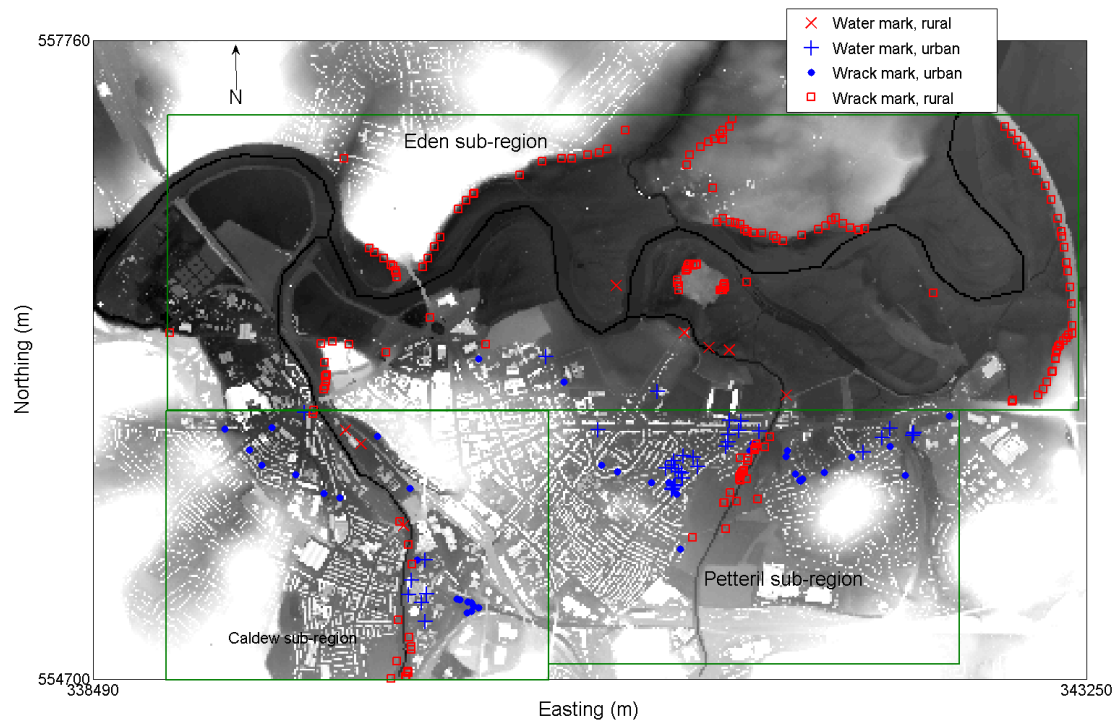


Figure 5.7. DEM of Carlisle area showing: geographical **sub-regions** of the study area (Eden, Caldew and Petteril); **observation types** (wrack marks - dots and squares and water marks - crosses); and **land use type** (urban - blue marker and rural - red marker).

#### 5.7.1 Evaluation of globally calibrated model

Comparisons are made using results of the Monte Carlo simulation between the global RMSE measure of model performance and the subjective measures described above. First the set of model realisations deemed behavioural under the conditions described in section 5.6 are examined to establish which would also be deemed behavioural under each of the seven subjective measures detailed above.

Table 5.4 gives an indication of how the global calibration scheme is dominated by observations located in rural areas in the Eden sub-region; almost all the behavioural realisations under a global scoring method are still deemed behavioural when scored against only observations in the Eden sub-region or only rural observations. Conversely, when scoring against urban observations or only those in the Caldew sub-region there is much less agreement, with fewer than half of the behavioural model realisations under a global scheme included. Does this highlight possible inadequacies in the globally calibrated model?



Table 5.3. Subjective model evaluation categories.

<b>Categorisation</b>	<b>Category</b>	<b>Number of Observations</b>	<b>Notes</b>
<b>Global (all observations)</b>		263	
<b>Sub-region</b>	Eden	139	Comprises the main flood plain of the River Eden and covers the entire northern section of the study area. Over half of the observations are included, but the vast majority of those are categorised as 'rural'. Only contains 4 'urban' measurements.
	Caldew	46	Mixture of wrack and water marks across rural and urban areas.
	Petteril	78	Contains a significant cluster of urban water marks. Also encompasses many other well distributed urban observations.
<b>Land use type</b>	Urban terrain	79	Not all urban areas that were inundated are well covered by observations.
	Rural terrain	184	The majority of rural observations are collected along the northern bank of the Eden flood plain and along the bank of a motorway at the eastern edge of the study area.
<b>Observation type</b>	Wrack marks	217	Wrack marks significantly outnumber the water mark observations. This may be because wrack marks are more evident or abundant, but is also due to the focus of one of the survey teams on mapping flood extent rather than water levels (Horritt et al., 2010) so they were not looking for evidence of peak water levels on vertical surfaces.
	Water marks	46	

Table 5.4. Subjective evaluation of model realisations deemed behavioural under global RMSE score.

<b>Categorisation</b>	<b>Category</b>	<b>Best RMSE (m)</b>	<b>Mean RMSE (m)</b>	<b>Proportion of realisations still deemed behavioural<sup>2</sup>.</b>
<b>All observations</b>		0.243	0.334	266
<b>Sub-region</b>	Eden	0.186	0.258	262 / 266
	Caldew	0.264	0.455	125 / 266
	Petteril	0.260	0.346	216 / 266
<b>Land use type</b>	Urban	0.304	0.432	121 / 266
	Rural	0.200	0.278	264 / 266
<b>Observation type</b>	Wrack marks	0.204	0.307	258 / 266
	Water marks	0.298	0.427	132 / 266

With reference to the Caldew sub-region, the lack of agreement in behavioural parameter sets can at least be partially explained by the fact that the flooding would have primarily been caused by the Caldew itself, so in some sense this result doesn't show a great amount except that it may be possible to treat the Caldew inundation as a separate event that could be modelled separately.

An interesting distinction is the divergent results between scoring against urban and rural observations. The RMSE of best performing simulations are considerably lower when scoring against observations in urban areas. The multiple specific difficulties of urban flood modelling such as the localised hydraulic effects and unusually low or high roughness figures are discussed in section 3.3.2, and these could explain the divergence. Additionally, as discussed in section 4.3.1, the inaccuracies in the observational data will also tend to be greatest in built-up areas, further adding to the uncertainty associated with a calibration based on just the sub-set of urban

<sup>2</sup> This is the number of simulations with an RMSE less than 0.411 m out of the 266 that were considered behavioural when measured against all observations.

observations. This effect is analysed in more detail in section 5.8 where a model calibration scheme based solely on observations from urban areas is compared with the globally calibrated model.

Another point highlighted by the numbers in table 5.4 is the proportion of behavioural realisations when scoring the model just using water marks. The overall number of wrack marks greatly exceeds the number of water mark observations, so a global calibration method will be dominated by the wrack mark observations. A divergence in the results when comparing water marks might suggest a systematic bias between the two types of observation. However, as shown in chapter 4, any apparent systematic difference between observation types is most likely entirely due to a dense cluster of water marks in an urban area to the west of the River Petteril see figure 4.12. This cluster of observations was measured to be consistently higher than simulated water levels from model realisations which, when evaluated ‘globally’, perform well. The reason for this apparently ‘raised’ cluster of water marks is difficult to attribute to a single cause; one explanation is that localised inundation here was exacerbated by flooding from a non-fluvial source such as upsurge from the urban drainage system which is not simulated by the hydraulic model (see chapter 4 for a more detailed discussion).

#### 5.7.2 Spatial variation in uncertainty highlighted by subjective sampling schemes

In this section, the extent of variation between maximum and minimum water extent and level is presented giving a spatial visualisation of how uncertainty could vary under different model cross-validation sampling schemes. Alternative sets of behavioural model realisations are selected using the categorisation schemes listed above. Since the definition of the GLUE likelihood function is unchanged from that defined in section 5.6, this section is not a comparison of alternative calibration schemes. Instead the purpose of this investigation into the spatial variation of uncertainty is a qualitative guide to whether any full subjective calibration schemes are worth implementing.

Figure 5.8 shows the probabilistic flood maps created using the urban sampling scheme (figure 5.8 a) and the Caldew sub-region sampling scheme (figure 5.8 b) for

comparison with figure 5.6 in section 5.6 created using the global calibration scheme. The differences between the probabilistic flood map based on the urban sampling scheme and the globally calibrated map (figure 5.6) are subtle and hard to identify using these maps. However the map sampled only on the Caldew sub-region shows a noticeable increase in uncertainty away from the Caldew region.

In order to demonstrate further the differences between the various sampling schemes, the individual simulations resulting in the maximum and minimum water level and extent are identified. Figure 5.9 shows these maxima and minima overlaying the Carlisle DEM for the three sampling schemes: global, urban locations only and the Caldew sub-region

As can be seen in figure 5.9, the greatest uncertainty is in the urban areas where, under the global calibration scheme, there are areas showing a wide difference between maximum and minimum simulated water levels even though only the subset of model realisations deemed behavioural are used. By ignoring the performance of the model in rural areas, the uncertainty in urban areas seems somewhat reduced (figure 5.9, c and d), with apparently little effect on the uncertainty elsewhere. This may suggest a deficiency of the model when simulating flooding in the urban areas that could be at least partially addressed using an alternative calibration scheme that gives greater weight to urban observations. Section 5.8 describes the implementation of such an urban calibration scheme. The maps based only on the sample of observations from the Caldew sub-region seem to show little or no reduction in uncertainty even near the Caldew when compared with urban sampling scheme. This suggests that this localised sampling scheme provides no additional information on model performance beyond that which the urban sampling scheme provides, probably because the subset of Caldew observations is largely urban. Consequently, an alternative calibration scheme based only on observations from the Caldew sub-region is not considered.

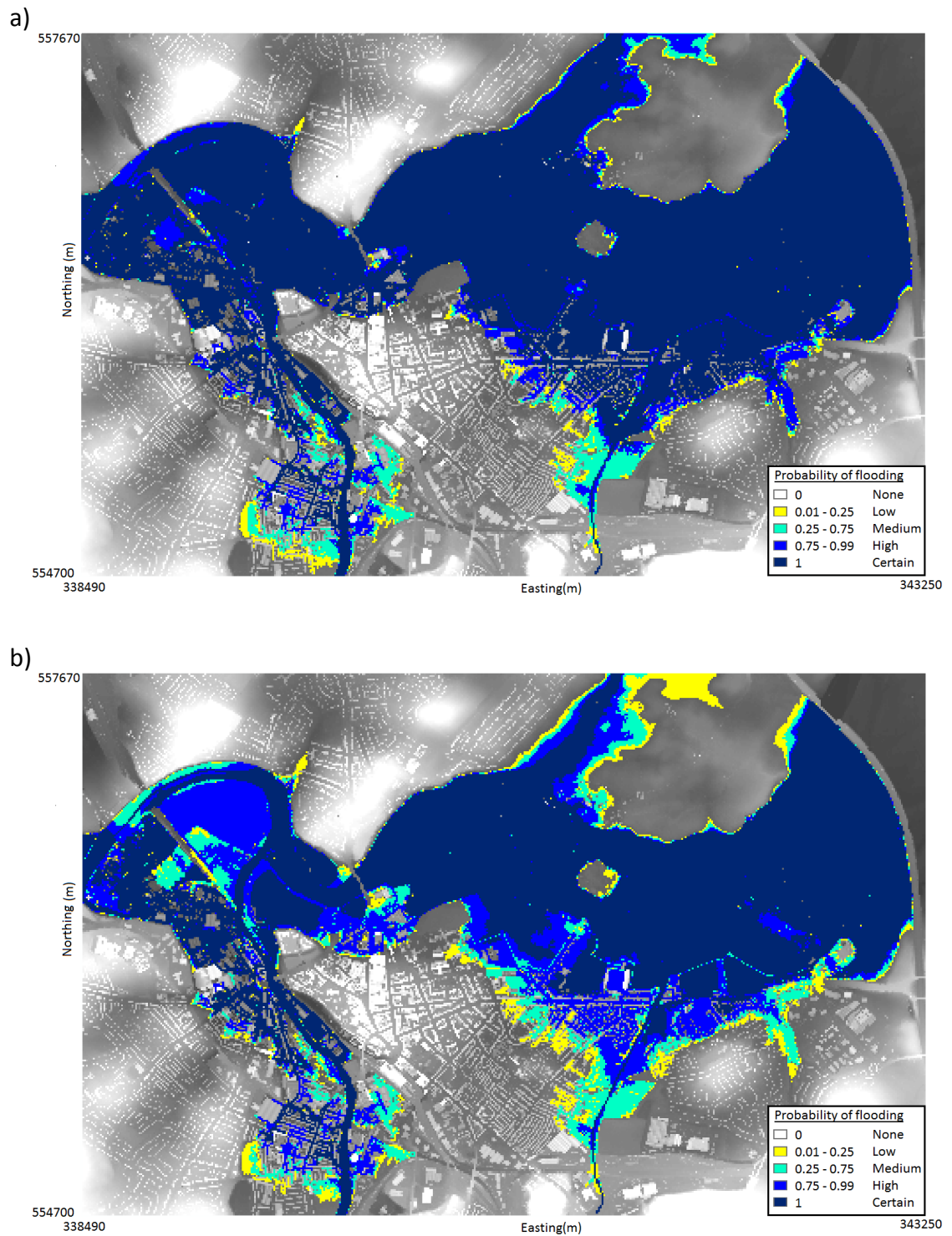


Figure 5.8. DEM for Carlisle overlaid by probabilistic flood map for the January 2005 flood: a) using only observations in urban locations; b) using only observations in the Caldew sub-region (see figure 5.7). Pixel colour represents probability of inundation and is not an indication of flood depth.

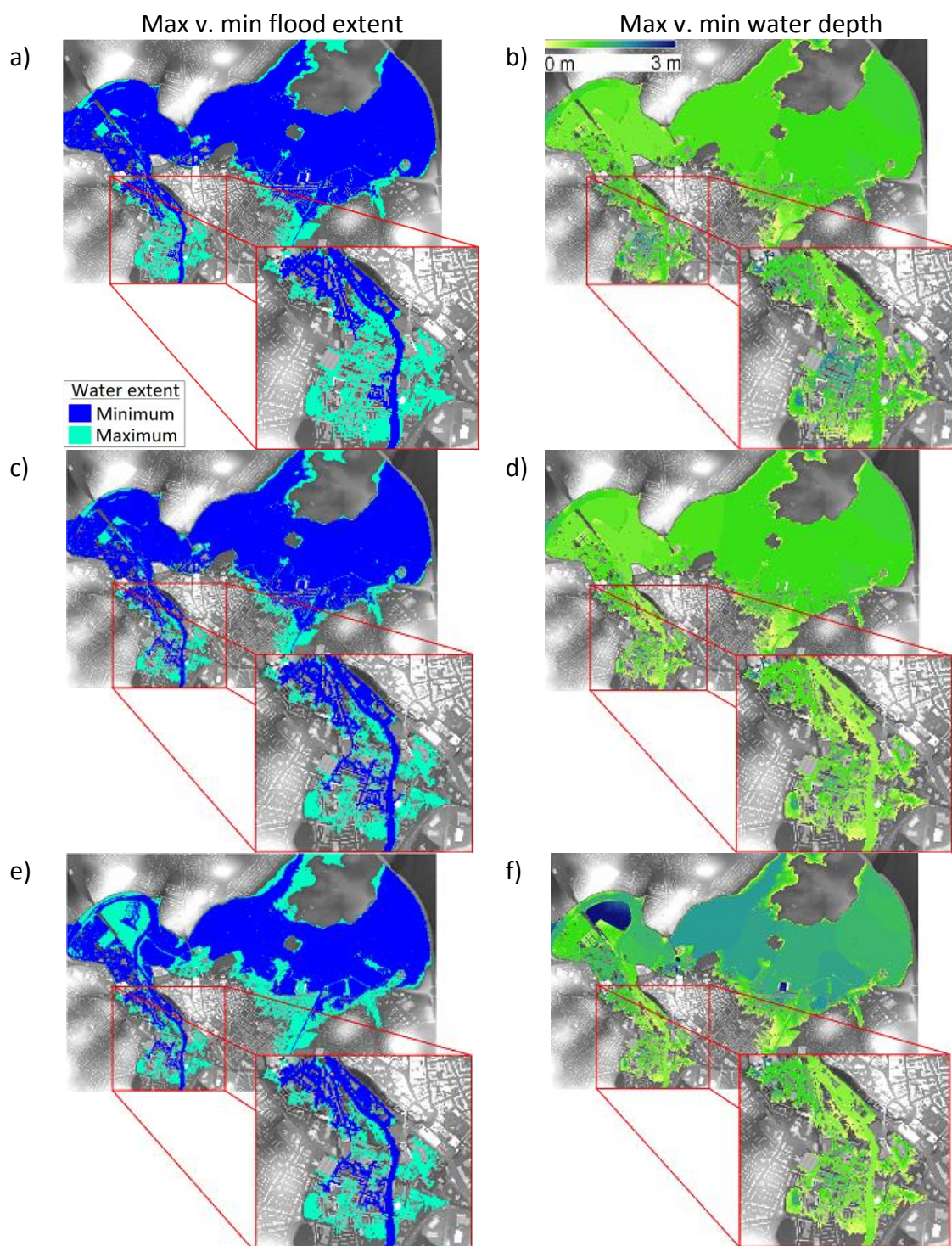


Figure 5.9. Variation in uncertainty as represented by the difference between minimum (dark blue) and maximum (light blue) simulated water extent (a, c and e) and the difference between maximum and minimum water depth (b, d and f) (blue shades represent higher uncertainty in water depth). a and b show the uncertainty under the global calibration scheme, c and d use only observations in urban locations and e and f use only observations in the Caldey sub-region (see figure 5.7).



## 5.8 Subjective model calibration

In order to implement an urban calibration scheme, the definition of a behavioural simulation needs to be altered to reflect the fact that we are only considering observational data from urban areas. Using the same principle as was used for the global calibration scheme (section 5.2), the best performing simple 1D simulation gives an RMSE (urban observations only) ( $E_{max}$ ) of 0.528 m. This is then used to identify which of the 1D/2D simulation parameter sets are behavioural under an urban calibration scheme, leaving 302 parameter sets out of the original 999. The total observational uncertainty  $U$  for urban observations is calculated using eq. 4.3 with a figure of 0.115 m for the observational uncertainty  $U_{obs}$  in urban locations (see figure 4.5). The new, urban, values for  $E_{max}$  and  $U$  are used in eq. 5.4 to define the new GLUE likelihood function for the urban calibration scheme and figure 5.10 shows the resulting probabilistic flood map of the January, 2005 event modelled using the urban calibration scheme.

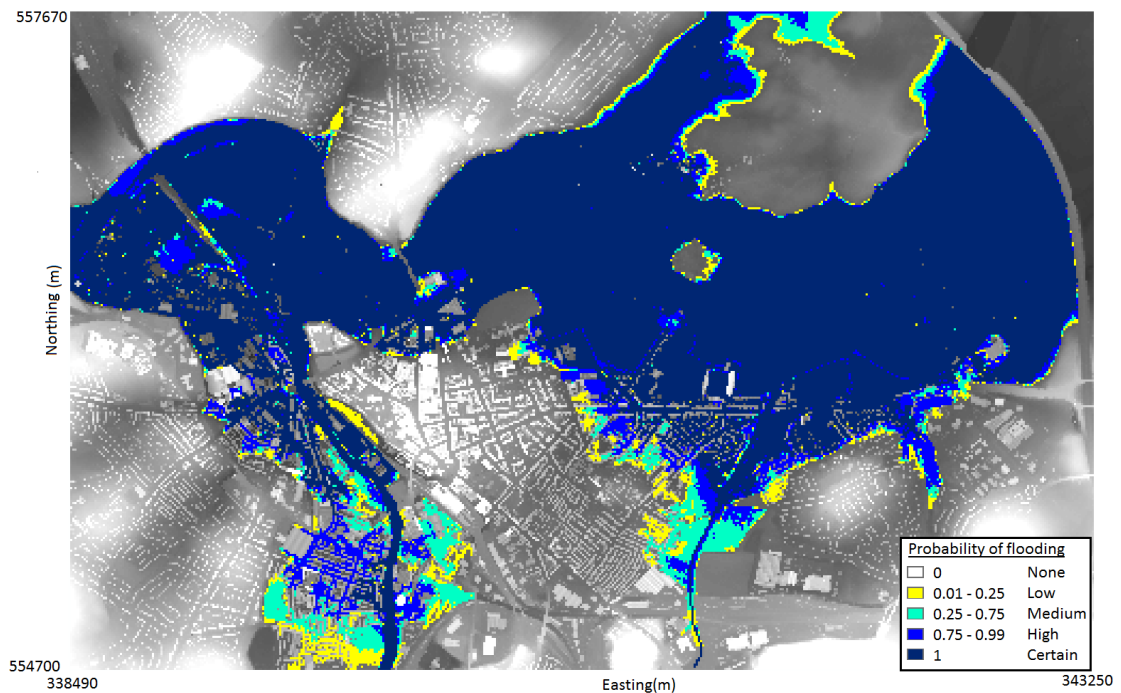


Figure 5.10. DEM for Carlisle overlaid by probabilistic flood map for the January 2005 flood model calibrated using an urban calibration scheme. Pixel colour represents probability of inundation and is not an indication of flood depth.

A visual comparison of figures 5.6 and 5.10 reveals little or nothing. Figure 5.11 shows only the difference in flood risk estimated by implementing the urban calibration scheme, i.e. it is a visualisation of the difference between figure 5.6 and figure 5.10. Although figure 5.11 does indicate the flood probability has changed somewhat in the urban areas around the Rivers Caldew and Petteril, it should be noted that the maximum absolute change in the probability of flooding is 0.24 with most pixels showing no change or a change in probability of less than 0.1.

To visualise the effect of implementing the urban calibration scheme, figure 5.12 shows the change in uncertainty between the probabilistic flood maps in figures 5.6 and 5.10. Pixels on probabilistic flood maps with a probability of flooding of 0.5 have the highest uncertainty, so a change of flood probability away from 0.5 towards either 0 (no chance of flooding) or 1 (certainty of flooding) is considered a reduction in uncertainty. Even in the urban areas there is no overall reduction in uncertainty gained by using the urban over the global calibration scheme.

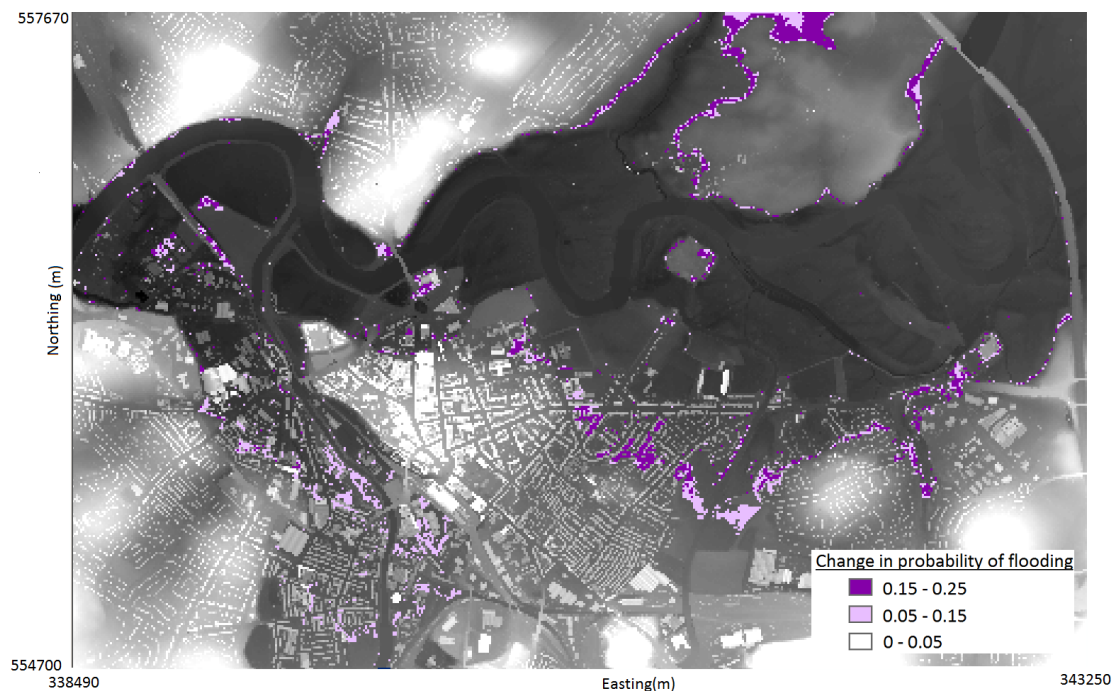


Figure 5.11. DEM for Carlisle overlaid by the change in flood probability by implementing an urban calibration scheme (figure 5.10) instead of a global calibration scheme (figure 5.6).



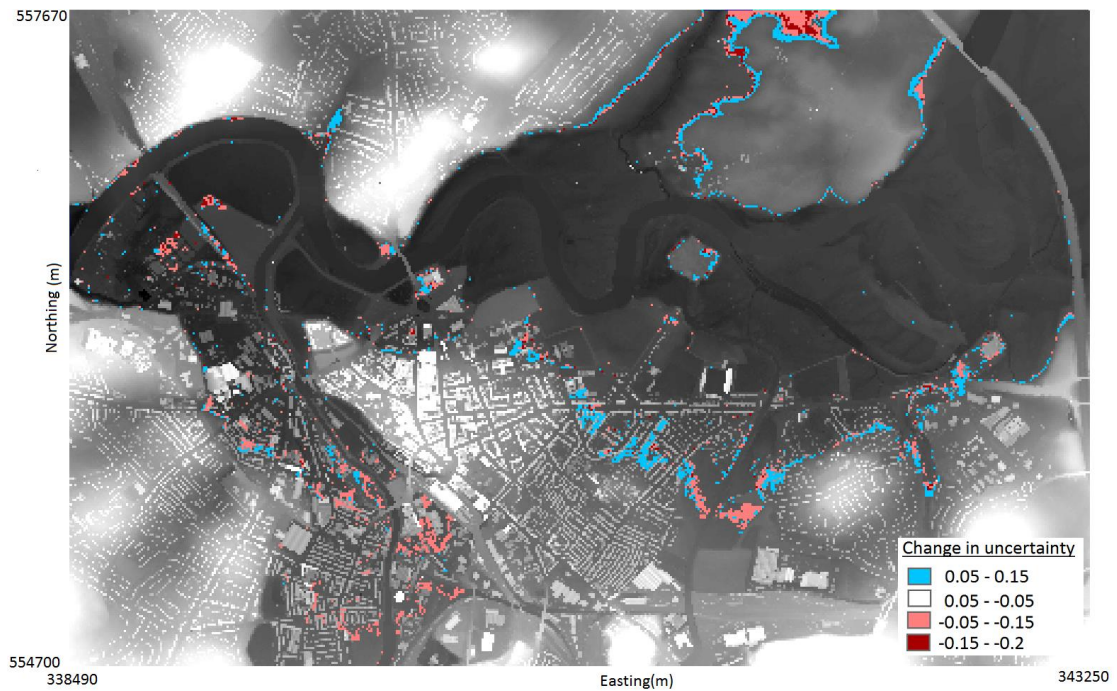


Figure 5.12. DEM for Carlisle overlaid by the increase (red pixels) and decrease (blue pixels) in flood risk uncertainty by implementing an urban calibration scheme (figure 5.10) instead of a global calibration scheme (figure 5.6).

## 5.9 Conclusion

This chapter has given a detailed description of running a Monte Carlo simulation of 999 model realisations of a LISFLOOD-FP model of the January 2005 flood in Carlisle. Using the GLUE methodology to calibrate the flood model has allowed the creation of probabilistic flood maps that give a visualisation of the spatial distribution of uncertainty due to the observational data, model parameters and structure. However, the calibration of the model using all data, equally weighted is just one of many calibration schemes that can result in differing probabilistic flood maps. It may seem a natural and objectively right to give equal weight to all observations, nonetheless it should be recognised that it is a choice and therefore a subjective choice made by the modeller. Risk based calibration schemes that give greater weight to the areas of high risk (where risk is defined as hazard  $\times$  consequences) may produce probabilistic flood maps that are of greater value to those affected by flood risk. In section 5.7 a cross-validation process of the model was performed using 3 different subjective sampling strategies. The sampling strategy based solely on flood extent observations in urban

areas appeared to highlight a localised deficiency of model performance in the areas deemed highest risk (Posthumus et al., 2009). However in section 5.8, when a calibration scheme that only used observational data points in urban areas was fully implemented using the same criteria as the global calibration, little change in flood probabilities and no noticeable reduction in uncertainty resulted. It seems that in this case, when the uncertainty in the observational data is considered, the attempt to employ a more specific, risk-based calibration scheme gives no beneficial reduction in uncertainty in areas of higher vulnerability.

In the following chapters the probabilistic flood maps to match the so called 'design flood' frequencies of 0.01 and 0.001 AEP are generated using simulations of the January 2005, Carlisle event using a global calibration scheme with the hydrographs scaled to match the peak discharge of the design floods. The resulting estimates of uncertainty in the extent of the design floods and the importance placed on them emphasise the significance of the subjective choices made, either consciously or sub-consciously by those involved in creating hydraulic flood models.

## Part 2. FLOOD FREQUENCY ANALYSIS

## Chapter 6. Review of flood frequency analysis

### 6.1 Introduction

The techniques described in chapters 4 and 5 for simulating floods and assessing the associated uncertainty are only the first step in producing a flood model with predictive capability that can be of use in for flood risk assessment (FRA). Simulating a previous flood event is of limited use if the likelihood of a similar flood happening again soon is not known. Practitioners of flood risk do make use of information they have on the extent of the largest known flood in an area (interview, Flood Risk Manager, Environment Agency) and sometimes estimate a theoretical flood such as the ‘valley filling event’ or the ‘probable maximum flood’ (Acreman, 1989), but it is now common practice and indeed required by the European Commission (2007) to provide quantified fluvial flood risk assessments. This science of flood frequency analysis is predicated on knowledge of the likely distribution of the discharges in the local rivers. The outcome is typically stated in terms of an estimate of the peak discharge of a flood with a certain likelihood, sometimes referred to as a ‘design flood’ (Shaw et al., 2010). The most commonly used ‘design flood’ is that with a 0.01 annual exceedance probability (AEP) also referred to as a 1% annual exceedance percentage or, more familiar may be the term “the 100 year flood” (see Bell and Tobin, 2007 for a discussion of this phrase). In probabilistic terms the 0.01 AEP flood is the flood that has a 1% chance of being equalled or exceeded in any year.

Whereas the uncertainty analysis in the previous two chapters (4 & 5) was concerned with quantifying and minimising the epistemic uncertainties arising from the observational data, discharge data and digital representations of terrain, chapters 6 & 7 deal with the aleatory uncertainties arising from the stochastic environmental processes causing and characterising flood events. These elements of flood risk analysis can only be represented probabilistically through the use of distribution functions which typically need to be modelled using Monte Carlo simulation techniques. This chapter provides background for the techniques of extreme value statistics used in the following chapter: “Estimating flood frequencies in Carlisle” and can be skipped by those with a familiarity of the subject.

## 6.2 River flow and flood frequency analysis

The Environment Agency operates roughly 750 river gauges in England and Wales storing measurements of stream flow every 15 minutes, many of the record lengths are 40-50 years, with a few up to 100 years (Environment Agency, 2010c; 2011c). Although the measurements from river gauges and the discharge estimates calculated from them are uncertain with inaccuracies that may be exaggerated when discharge is particularly high and are likely to show seasonal variation, they provide an invaluable source of information for characterising the behaviour of streams and rivers. But as Shaw et al. (2010) point out, the gauged data are only a very small sample of the overall discharge and needless to say, the sections of data most useful to those concerned with flooding are the highest extremes from which the flood frequencies can be estimated.

The key metric to define the magnitude of a flood event is the peak discharge. If the relationship between the exceedance probability and the peak discharge of a flood is known then the two can be plotted to give a flood frequency curve. The following sections review some of the many techniques and methods used to derive uncertain flood frequency curves from the limited available data.

The practicalities of defining the flood frequency curve are far from straightforward; the accuracy for the curve is heavily dependent on the accuracy and availability of the hydrological data at the site of interest and a number of different methods might be used to estimate the flood frequency curve which may give widely varying results. Flood frequency estimation is an inexact science where many sources of uncertainty should be considered by the practitioner whose job it is to apply the most appropriate method or combination of methods to estimate the flood frequency curve within reliable confidence limits. Furthermore, the nature of extreme value statistics dictates that the uncertainty increases with the return period (Shaw et al., 2010), such that in calculations of flood damage estimations, the uncertainty in the flood frequency curve dominates the overall uncertainty as return periods exceed 100 years (see for example Apel et al., 2008; Merz and Thielen, 2009).

In general, the methods of performing flood frequency analysis fall into two distinct camps. The ‘statistical method’, discussed in detail in this project, is based on the use of extreme value statistics to estimate flood return periods beyond the length of the available river gauge time series (IH, 1999). The second approach, known as the ‘rainfall-runoff method’ makes the use of a hydrological rainfall-runoff model for the catchment to estimate river flows at the site in question (IH, 1999). The flood frequencies are then derived by driving the hydrological model with a synthetic set of extreme rainfall events. Examples can be found in Lamb (1999); Li et al. (2014); Loukas (2002); Rahman et al. (2002); Saghafian et al. (2014). The synthetic precipitation time series can be extended to cover many thousands of years giving an equivalently long time series of extreme discharge estimates from which the flood frequency curve is estimated. Since the synthetic time series is ultimately based on the statistical properties of known storms (England et al., 2014; Neal et al., 2012), it is misleading to think of only one of the approaches to flood frequency estimation as ‘statistical’. It is also perhaps wrong to think of the two approaches as completely distinct; there is no reason why a hybrid approach cannot be employed. Indeed, it may be the case that the hydrological model is calibrated using peak flow data from the river gauges (Kjeldsen, 2007).

### 6.3 Extreme value statistics

The estimation of flood frequency curves from the river gauge readings falls into an area of statistics known as extreme value theory which is concerned with extreme deviations from the median. The theory of extreme values was pioneered in the first half of the twentieth century by the eminent statisticians L.H.C Tippett and R. A. Fischer (Daniels, 1982), and subsequently codified in the 1958 book ‘Statistics of Extremes by the German mathematician E.J. Gumbel (Gumbel, 1984). The Gumbel distribution is still in use today as a case of one of several families of distributions used in parametric statistical modelling. The selection of the most appropriate parametric model is paramount with extensive literature available on the methods of model and parameter selection to fit the T-year event based on time series samples of less than T years. See for example books by Castillo et al. (2005), De Haan and Ferreira (2006) and

Reiss and Thomas (2007) for examples covering such areas as extreme environmental hazards, catastrophic engineering failures and the behaviour of financial markets.

Returning to the specific problem of determining the probability of rare floods, there are two methods to sampling the data used to identify and fit the tail of the distribution. The block sampling method slices up the original data into equally sized blocks and build the sample from the maximum value in each block, in the case of time series of river discharge the blocks are typically one year<sup>3</sup>, with the maximum discharge figure being the annual maximum (AMAX). The second method builds the sample of all values over a certain threshold and is known as the peak (or point) over threshold (POT) method. For return periods of less than 10 years, the two sampling methods can result in different probability distributions, but beyond 10 years the differences reduce as the return period increases and the AMAX method is most commonly used (Shaw et al., 2010) which is the case in this project.

#### 6.4 History of flood frequency estimation in the UK

In the UK, the Flood Studies Report (FSR) (NERC, 1975), published in 1975 was an extensive body of work originally commissioned by the Institute of Civil Engineers to provide guidance and proposals on flood estimation methods across the British Isles (Sutcliffe, 1978). As well as describing methods for estimating flood frequency curves from discharge data, the FSR covered estimation methods for hydrographs resulting from 'design storm' events, depth-duration frequency curves for rainfall and estimates of possible maximum precipitation (PMP) for all areas of the country (Sutcliffe, 1978). These methods were used extensively, not only by the National Rivers Authority (the predecessor to the Environment Agency) for planning flood defences but also, for example, by engineers designing dam spillways that need to withstand 1 in 10,000 year rainfall events(Cluckie and Pessoa, 1990).

The FSR recommends using the generalised extreme value (GEV) distribution (Hosking et al., 1985b), with some discussion on the use of regional data to enhance the estimations. The difficulties of selecting the most appropriate distribution and

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<sup>3</sup> The 'year' for hydrological purposes in the UK is defined as the 'water year' which begins on 1<sup>st</sup> October, deemed to be the time that groundwater storages are most usually low.

estimating the goodness of fit are discussed and a formula is suggested for the standard error of the flood return period (Sutcliffe, 1978). Whilst the methods and algorithms in the FSR were widely accepted and praised as highly effective at the time, as the length of river gauge time series grew and more powerful computers became available, new and improved curve fitting methods highlighted deficiencies in the FSR methods (Hosking et al., 1985a). Additionally, given the limitation on the availability of computing power at the time of the FSR it is perhaps unsurprising that uncertainty estimation methods based on multiple sampling was not prioritised (Hosking et al., 1985a).

In 1999 the Flood Estimation Handbook (FEH) was produced by the Centre for Ecology and Hydrology (CEH) as a replacement to the FSR (IH, 1999). The FEH was another significant five-volume work, this time with accompanying software on floppy disk (or CD ROM). Included in the FEH is, for example, a new regression model for estimating flows at un-gauged sites based on the use of several catchment descriptors to identify suitable 'donor sites' (Kjeldsen and Jones, 2007). The methods in the FEH promote more complex methods of estimating flood frequencies for example more emphasis is placed on the use of site pooling to generating a virtual time series of several hundred years which would be longer than the target return periods (IH, 1999). However, rather than resulting in more accurate flood frequency estimates, it seems the additional complexity, combined with a perceived decline in technical competence, may have given rise to confusion and antipathy as the users struggled to understand the procedures and reconcile the results with the FSR methods that they had come to rely on (Porter, 2010). For example, anecdotal evidence suggests that when using site pooling, the lack of homogeneity between sites was said to counter any benefit over single site analysis when the on-site discharge record is longer than approximately 25 years.

Refinements to the methods have continued with the latest software release being in 2008. Notable changes include a new way of selecting sites for use in pooling and a new method of site pooling is introduced (termed Enhanced Single Site analysis rather than Pooled Site Analysis) in which far greater weighting is placed on the site of interest over the pooled sites (Kjeldsen et al., 2008). This swing back towards



emphasising the on-site records is perhaps a suggestion that the process of identifying the best way of estimating the flood frequency curve for a particular site may be more art than science. Certainly local knowledge of the catchment and river channel are invaluable and choices made should enable the practitioner to make the best use of all the available data (see for example Lane et al., 2011a). Regardless of the process followed it is clear that there will be significant uncertainty in the resulting calculations of flood return periods which, although difficult to quantify, should not be ignored. The next section covers the statistical mathematics used to estimate the flood frequency curves using annual maximum records from river gauges.

### 6.5 Analysis of an annual maximum series

In terms of a time series of AMAX records, for any given AMAX magnitude,  $X$ , the AEP of  $X$  is  $P(X)$  and is defined as:

$$P(X) = r/N \quad (6.1)$$

Where  $r$  is the number of times  $X$  is exceeded in  $N$  years, given that  $N$  is large. The return period of  $X$  denoted by  $T(X)$  is simply  $1/P(X)$ .

In terms of the cumulative distribution function for  $X$ ,  $F(X)$ , being the annual probability of  $X$  not being equalled or exceeded:

$$F(X) = 1 - P(X) = \frac{T(X) - 1}{T(X)} \quad (6.2)$$

Showing the straightforward relationship between the return period, annual exceedance probability and cumulative probability.

Given a sufficiently long hypothetical AMAX time series, say 10,000 years it would be possible to use equation 6.2 to obtain direct statistical estimates for peak flood discharges up to and exceeding return periods of 1,000 years. However, in reality the length of the AMAX time series is much shorter so statistical curve fitting methods need to be employed to fit the available data to a probability distribution function (PDF). Since there is no a priori definition of the 'correct' distribution (Apel et al., 2008), the first step is to select which distribution(s) to use.

### 6.5.1 Choice of extreme value distributions

There are several different extreme value distributions (EVD's) for defining the flood frequency curve from an AMAX data series that have been used throughout the world (Cunnane, 1989). Several of the commonly used distributions in flood frequency analysis (e.g. generalised extreme value, generalised logistic, Pearson type III) are characterised by three parameters defining the *location*, *scale* and *shape* of the curve (examples include: Chowdhury et al., 1991; Lim and Lye, 2003; Martins and Stedinger, 2000; Milly et al., 2002; Morrison and Smith, 2002; Saf, 2009; Singh and Guo, 1995). However 2 parameter distributions such as the Gumbel (or Extreme Value Type I) (Gumbel, 1941) and Weibull (or Extreme Value Type II) (Boes et al., 1989) distributions are deemed adequate in places (e.g. Fill and Stedinger, 1995; Francés, 1998; Francés et al., 1994; Rossi et al., 1984; Yue et al., 1999). In some situations the additional parameterisation of the 4 parameter Kappa (Hosking, 1994) and the log Pearson type III (Bobée, 1975; Griffis and Stedinger, 2007a; Griffis and Stedinger, 2007b; Griffis and Stedinger, 2009) distributions, even the 5 parameter Wakeby, which is flexible enough to mimic most other distributions (Houghton, 1978), have been deemed appropriate (e.g. Kumar and Chatterjee, 2005; Norbiato et al., 2007; Rahman et al., 2015). When analysing a POT data series, the three parameter generalised Pareto distribution is normally considered most suitable (Naden, 1992; Papastathopoulos and Tawn, 2013; Wang, 1991), although alternative approaches such as the use of power-law statistics have also been proposed (Kidson and Richards, 2005; Malamud and Turcotte, 2006; Malamud et al., 1996; Turcotte and Greene, 1993).

Official procedures from the authorities of the country in which the river system resides may provide recommendations for the distributions which are considered best to fit the majority of sites. In the UK, for example, the Flood Estimation Handbook (vol. 3) recommends using the generalised logistic (GL or GLO) distribution (IH, 1999), which, together with the generalized extreme (GEV) distribution is thought to be a satisfactory fit for almost all of the 602 gauged locations (Kjeldsen et al., 2008). Conversely, in the United States, Bulletin 17B from the United States Water Resources Committee (Kirby and Moss, 1987; USWRC, 1982) recommend the use of the Log-Pearson Type III (LP3) distribution (Bobée and Ashkar, 1991; Reis and Stedinger, 2005;

Vogel and McMartin, 1991) which has also been adopted in other countries such as Australia (McMahon and Srikanthan, 1981; Pattison, 1977). The lognormal distribution is favoured in China (Singh and Strupczewski, 2002). However, given the huge range of catchment and regimes types and sizes in all but the smallest countries, it should not be supposed that one or even two distribution types can be a good fit for all locations (see discussion in Stedinger and Lu, 1995). Mathematical details of all the distributions used to describe flood frequencies based on AMAX records can be found in Haan (1977), Cunnane (1987), Stedinger et al. (1992), Hosking and Wallis (1997), IH (1999), Katz et al. (2002), Reiss and Thomas (2007), and numerous other texts.

### 6.5.2 Parameter fitting

Given a limited set of AMAX data, an obvious choice of distribution may or may not present itself, or possibly the choice is dictated by the procedures recommended by the relevant national authorities. In any event, once a candidate distribution is selected the next stage is to identify the parameter set(s) that best fit the available data.

Just as there are several alternative extreme value distributions, so there are a number of methods for fitting the parameters. Non mathematical descriptions of some of the commonly used methods are provided below, see texts such as Landwehr et al. (1978) Greenwood et al. (1979) Landwehr et al. (1979) Stedinger et al. (1992), Hosking (1990) Hosking and Wallis (1997), IH (1999) and Reiss and Thomas (2007) for the full derivations.

### **Method of Moments**

The traditional way of describing a probability distribution of a random variable is through the use of the population moments of distribution (Hosking and Wallis, 1997). The first moment is the expected value, or mean ( $\mu$ ) of the random variable, with higher order moments being derived from the expected values ( $E$ ) of the random variable( $X$ ) raised to higher powers:

$$\mu_r = E(X - \mu)^r, \quad r = 2, 3, \dots \quad (6.3)$$

From this set of population moments, the various properties are defined that provide information about the distribution (Dingman, 2002). For example the *variance* ( $\sigma^2$ ), a measure of a spread of a distribution about its centre, is equal to the second population moment. Further properties such as the dimensionless *coefficient of variation*, *skewness* and *kurtosis* of a distribution can be found from simple equations involving the second, third and fourth order population moments. The population mean, variance and skewness and kurtosis are then used to calculate the parameters for many of the commonly used EVD's listed in section 6.5.1 using equations specific to the selected probability distribution (Dingman, 2002).

Quantities analogous to the population moments are deduced from the available sample data (of size,  $n$ ), these are referred to as the sample moments (Reiss and Thomas, 2007). The sample mean can be estimated using:

$$\bar{x} = (\sum_{i=1}^n x_i) / n \quad (6.4)$$

And, following equation 6.3, the higher order sample moments ( $m_r$ ) might reasonably be defined by:

$$m_r = (\sum_{i=1}^n (x_i - \bar{x})^r) / n \quad (6.5)$$

Giving estimates for the population moments such that  $\mu_r = m_r$ . However, this method is known to be likely to result in biased estimates for the higher order population moments resulting in unreliable estimates for the variance, standard deviation, CV, skewness and kurtosis (Hosking and Wallis, 2005).

### **Maximum-likelihood estimators (MLE)**

Methods for estimating distribution parameters by finding the values that maximise the probability of obtaining the data from the parameterised distribution are known as maximum-likelihood (ML) estimators (Dingman, 2002). In some cases an MLE method is very similar to the use of moments, and in the case of some distributions (for example the normal distribution) are known to produce well defined estimates (see for example Reis and Stedinger, 2005). However for more complex problems the MLE

method can be intractable and since the method is justified on the basis of large sample theory, it is often considered inappropriate for the limited sample size often available in flood frequency analysis (Hosking et al., 1985b).

### **The methods of L-Moment estimation and probability weighted moments**

A related approach to the method of moments is the L-moment estimation method. This method makes use of '*L-statistics*' from linear combinations of the ordered set of available data (Hosking, 1990). The L-moment estimation method is used extensively in flood frequency analysis because it is generally considered to give unbiased distribution parameter estimates that are robust against outliers even with small data samples (IH, 1999; Reiss and Thomas, 2007). In many cases the method of L-moments used with modest sample sizes has performed best when compared to other methods of parameter estimation including maximum likelihood methods (Hosking and Wallis, 1987) that can require complex numerical solutions (Hosking et al., 1985b).

The use of L-moments as a way of summarising the shapes of distributions is derived from the 'probability weighted moments' (PWM) method described by Greenwood et al. (1979). Whilst probability weighted moments can be used directly to estimate parameters of probability distributions (for example see Hosking and Wallis, 1987), it is not easy to derive useful estimates for the scale and shape parameters. However, L-moments, which are calculated simply from certain linear combinations of the probability weighted moments, can be used to give parameter estimates of most probability distributions (Hosking, 1990). The method of L-moments is recommended for flood frequency analysis in the UK by the Institute of Hydrology (IH, 1999).

### **Other methods of parameter estimation**

Given the range of probability distributions, variation in length and quality of discharge time series and disparate goals of flood frequency estimation practices, it is unsurprising that there have been many other parameter estimation methods proposed. Some of these are original methods, once popular due to their simplicity and tractability, for example Jenkinson's (1969) method of sextiles. Others are variations of established methods for example Cohn et al.'s (1997) expected moments

algorithm (EMA) that allows historic flood information to be combined with systematic gauge data using iterative methods of moments and Raynale-Villasenor's (2011) alternative PWM method.

### **Bayesian methods**

Bayesian inference describes the method of using Bayes' rule to infer uncertain parameter values for a distribution function of a random variable using all the available observations of that random variable (Bertsch-McGrayne, 2011). In mathematical form Bayes' rule is written:

$$p(\theta|D) = \frac{\ell(D|\theta)p(\theta)}{\int \ell(D|\theta)p(\theta)d\theta} \quad (6.6)$$

For any probability distribution with parameters  $\theta$ , such that  $p(\theta)$  is the prior distribution (or initial belief) and  $p(\theta|D)$  is the posterior distribution (new and improved belief) after having observed the additional data,  $D$ .  $\ell(D|\theta)$  is the likelihood of the data ( $D$ ) conditional on the parameters ( $\theta$ ).

The use of Bayes' methods for flood frequency analysis is attractive because it provides a way of estimating the parameters of distributions using data from multiple sources and of updating those estimates as new data becomes available. However, although equation 6.6 appears relatively simple, the integral denominator often has no analytical solution and the expression of the posterior distribution can become intractable as multiple sources of uncertain data are included (Lunn et al., 2013; Viglione et al., 2013). This means numerical methods, such as running Markov Chain Monte Carlo (MCMC) simulations are normally required to estimate the posterior distributions (Robert and Casella, 2004). This is not normally a hindrance to the researcher using modern computing power, and there are many recent articles describing the use of Bayesian methods to infer flood frequency curves using a combination of systematic data from river gauges, historical flood records (Reis and Stedinger, 2005), palaeo-flood evidence (O'Connell et al., 2002), output from hydrological rainfall-runoff models (Viglione et al., 2013), regional information from related rivers (Reis et al., 2005) and expert knowledge of physically realistic parameter values (Martins and Stedinger, 2000). Further details and examples of the

use of Bayesian methods for flood frequency analysis and other environmental models can be found in chapter 7.

### 6.5.3 Goodness of fit tests

Goodness of fit tests can be applied to the parameterised probability distribution with the aim of getting an objective measure of the how well the distribution fits the sample of observational data. Widely used tests from applied statistics include chi-squared, Komogorov-Smirnov, and quantile-quantile plots (Hosking and Wallis, 1997). However concern over the applicability of these familiar tests to the small samples typical in flood frequency analysis encouraged the design and use of tests specific to hydrologic applications (Laio, 2004). For example: Vogel (1986), Vogel and Martin (1991) and Heo et al. (2008) make use probability plot tests; Chowdhury et al. (1991) and Fill and Stedinger (1995) describe multiple goodness of fit tests using L-moments designed for the GEV and Gumbel distributions; and Ahmad et al. (1988), Laio (2004), Viglione et al. (2007) and Heo et al. (2013) suggest tests based on Anderson-Darling statistics (Anderson and Darling, 1952). Hosking and Wallis (1997) propose their own test using regional averages of L-moment ratios and this test was recommended in the Flood Estimation Handbook as applicable across the UK (IH, 1999). Since then, concerns raised by Morris (2003) were addressed and a modified goodness of fit test (Kjeldsen et al., 2008) was implemented in later versions of the WINFAP-FEH software (WHS, 2014) recommended for used in the UK by the Environment Agency (2012). This modified version of the Hosking and Wallis test (1997) is used in chapter 6 to assist in selecting the most appropriate extreme value distribution to use for the Carlisle case study.

## 6.6 Regional frequency analysis

The methods described above to fit an extreme value distribution to a time series of AMAX or POT data introduce a significant source of uncertainty to the flood frequency curve due to the limited record length of the gauge data, this is referred to as the sampling error (Kjeldsen et al., 2014a). The FEH advise that estimates of floods from flood frequency curves derived solely from a time series from a single gauge should not be made for floods of return periods greater than half the length of the gauged record (WHS, 2009b). Unfortunately for practitioners, this rule of thumb would render

the use of the statistical method of flood frequency analysis pointless in most gauged locations for return periods greater than 60 years. A widely used method of effectively extending the gauged record at a site is to “trade space for time” (Van Gelder et al., 2001) by compounding the limited systematic gauge data at one site with data from ‘hydrologically similar’ sites; a method known as ‘regional frequency analysis’ (Hosking and Wallis, 1997).

Regional frequency analysis has been considered for flood frequency analysis since the 1970s (Hosking and Wallis, 1997) and has subsequently been used elsewhere in environmental sciences, for example analysis of extreme rainfall (Fowler and Kilsby, 2003; Norbiato et al., 2007), droughts (Clausen and Pearson, 1995) and extreme wave heights (Van Gelder et al., 2001). A comprehensive account of regional frequency analysis is given in Hosking and Wallis (1997).

The premise behind regional frequency analysis techniques is to create a virtual time series of AMAX records for a site of several hundred years, which, in theory, allows improved estimations of flood frequencies well beyond the length of the systematic gauged record at the site. The practice involves identifying a list of catchments which are considered similar to the subject catchment and, in some way, combining the flood frequency curves from different sites. This might be achieved using the ‘index flood’ method which involves treating the flood frequency curve as a product of the median flood ( $Q_{med}$ ) (the flood with a return period of 2 years) and a dimensionless ‘growth curve’ for the site. The peak discharge of a flood with a return period of  $T$  years is then given by multiplying  $Q_{med}$  by the point on the growth curve corresponding to a return period of  $T$  years; this is known as the  $T$ -year ‘growth factor’.

Regional data is routinely incorporated into flood frequency analysis in the USA using the methods set out in Bulletin 17B from the United States Water Resources Committee (USWRC, 1982). In the UK, the original Flood Studies report (NERC, 1975) recommended pooling data based on geographical regions (IH, 1999), but this practice was replaced in the flood estimation handbook by a pooling method based on catchment characteristics (IH, 1999), with algorithms provided in the associated



software to assist with the selection pooling candidates for the subject site (WHS, 2009a).

The 'catchment descriptors' used to inform the selection of pooling groups in the UK include: catchment area, average annual rainfall, base-flow index and standard percentage runoff (both from the soil classification), flood attenuation from reservoirs and lakes and the extent of urbanisation. The first two are generally considered to have the most influence and are consequently weighted highest in the pooling algorithm (Kjeldsen et al., 2008).

The catchment descriptors are compared to the descriptors of the subject site to give a measure of the distance in 'descriptor space' between the catchments (Kjeldsen et al., 2008). Generally, the catchments selected for the pooling group are those closest to the subject site in 'descriptor space' with the number of pooled catchments defined by the total number of years of gauged data available at the subject and pooled sites (WHS, 2009b). The recommendation given in the flood estimation handbook is that the total number of years of gauged data should be five times larger than the target return period (IH, 1999). However, adherence to this rule could lead to discontinuities in the flood frequency curve as the contents of the pooling group changes for longer return period (Morris, 2003). Subsequent research into the performance of pooling groups suggests that little is gained from pooling groups with a total of more than 500 AMAX records (Kjeldsen et al., 2008).

It is not straightforward to define the optimal algorithm for selecting the pooled sites or indeed, once the pooled groups are selected, to decide their influence on the calculation of L-moments for estimating the distribution parameters. For example the 'index flood method' assumes that flood frequency curves within the pooling group are of an identical shape, and just need to be scaled so the median floods ( $Q_{med}$ ) match (Stedinger and Lu, 1995) whereas the 'region of influence' method described by Burn et al. (1990) assigns a different set of weights for each parameter based on the site characteristics.

Regardless of the method of creating and using the pooled site data the resulting expanded data set of AMAX records cannot be considered equivalent to single time

series of accurate AMAX records for the site of interest. Although the pooling method may be designed to minimise the effect of heterogeneity between sites through the weighting scheme, such that the sites in the pooling group that are least similar to the site of interest (furthest away in 'catchment descriptor space') have the least influence on the parameterisation of the flood frequency curve. The effect of this is to shift the influence back to the 'at-site' gauge records (the gauge records for the site of interest) such that regional flood frequency analysis can be seen as the practice of finding the optimal compromise between reducing uncertainty in the parameterisation of the flood frequency distribution by expanding the data available data at the expense of increasing uncertainty by introducing heterogeneity.

Quantifying the uncertainty in the flood frequency curve due to site pooling is complex, partly due to covariance between overlapping AMAX time from geographically proximate sites (Kjeldsen and Jones, 2006). However, based on the assumption that a good pooling method will produce a growth curve similar to the true growth curve for the site of interest, the FEH in the UK provides a simple pooled uncertainty measure (PUM) which can easily be applied to quickly assess the performance of alternative pooling methods (Kjeldsen et al., 2008). The PUM works by comparing individual catchment flood frequency growth curves fitted to the GLO distribution using L-moments with the growth curve of the site of interest (Kjeldsen and Jones, 2009).

#### 6.6.1 Un-gauged sites

So far the methods described for estimating flood frequencies have been made on the assumption that there is an existing systematic gauge record available for the site of interest. But there are very many sites likely to be affected by flooding for which no systematic gauged record is available. Elsewhere the situation may be even worse; the UK constitutes a relatively small, densely populated landmass, but many countries have far more extensive river networks with fewer river gauges (Milly et al., 2005). There are, however, methods for estimating flood frequencies at un-gauged sites, albeit with generally, larger uncertainties. The starting point is to identify a gauged site that is hydrologically similar to the un-gauged site of interest to act as a 'donor-site' from which  $Q_{med}$  can be estimated (Hosking and Wallis, 1997). The growth curve can

be estimated in a similar way to that described above for gauged sites (IH, 1999). More recent approaches that combine the use of both regional and historical flood analysis can be found in Castellerin et al. (2005), Payraastre et al. (2005), Castellerin (2007), Gaume et al. (2010) and Nguyen et al. (2014).

### 6.7 Use of historic and palaeo-flood data

Records of floods that predate the systematic gauged record at the site of interest can provide additional information to the hydrologist when estimating flood frequencies. The data and evidence of the floods can take a variety of forms, for each of which the associated uncertainty will have to be considered separately. This makes it difficult to provide a generally applicable algorithm for combining non-systematic (pre)historic data with systematic gauge data that takes account of uncertainty (Kjeldsen and Jones, 2009).

In the UK, which has a rich source of historical archives dating back over 1,000 years, the original flood studies report (NERC, 1975) mentions the incorporation of historical data (Stedinger and Cohn, 1986), however there seems to be no systematic inclusion of historic data in flood frequency studies in the UK prior to the year 2000, although there are some isolated examples: Potter (1978); Sutcliffe (1978); McEwan (1987; 1990) and Acreman (1989).

A report published by the Centre for Ecology and Hydrology, UK in 2001 provided guidance for, and underlined the benefits of, incorporating historical data in flood frequency estimates (Bayliss and Reed, 2001), and there followed a project by the British Hydrological Society to collate a database of historical hydrological records (Black and Law, 2004). Since then there have been several studies making use of these sources (see, for example Black and Burns, 2002; Macdonald, 2013; Macdonald and Black, 2010; Macdonald et al., 2006; Williams and Archer, 2002), but a review published by Kjeldsen et al. (2014b) concludes that the potential for reducing the uncertainty in flood risk estimates in Europe through the use of historic data is still not being realised. In the USA, Bulletin 17B of the United States Water Resources Council (USWRC, 1982) does provide documentation on incorporating historic records which has been developed and improved in the subsequent decades (for examples, see Cohn

et al., 1997; Condie, 1986; Condie and Lee, 1982; Francés et al., 1994; Jin and Stedinger, 1989; Reis and Stedinger, 2005; Stedinger and Cohn, 1986).

The impact that the use of historic and prehistoric data has on the resulting flood frequency estimates has been a subject of dispute. For example: Hirsch (1987) warns of the danger of bias introduced by assuming the time series should start at the time of the first historical flood record; Hosking et al. (1985a) suggest the likelihood of wide inaccuracy and bias in records of historic events are just as likely to degrade as improve the flood frequency estimation; similarly Hosking and Wallis (1986a; 1986b) and Kuczera (1992) find little benefit in incorporating historic flood data across a wide range of sites and regions. However, there have been plenty of studies published that describe more successful incorporation of palaeo-flood (Benito and Thorndycraft, 2005; O'Connell et al., 2002) or historic (see Benito et al., 2004 for review) data or a combination of both (Sheffer et al., 2003; Thorndycraft et al., 2006). It would seem that the potential value of the non-systematic data depends not only on the extent and quality of the data available but also on the approach taken to make use of the data. A careful, subjective method that takes full account of the uncertainties due to the inaccuracy, possible bias and non-stationarity present in the historic data may be required.

When considering palaeo-flood information or records of historic floods for use in flood frequency analysis, it is desirable to infer as much information about the magnitude of the past floods as possible. Palaeo-flood studies concern the collection of physical flood data from events where there exists no human documented evidence (Brázdil et al., 2006). This typically involves the use of sedimentology and geomorphology techniques to search for evidence of deposits or erosion from previous events (see for example Li et al., 2013). The clues can then provide information about the extent and age of particular floods. Reviews of the subject can be found in papers by Benito et al. (2004) and Baker (2006).

Gathering information on historical floods lies at the intersection of the fields of history and hydrology (Brázdil et al., 2006). Often the researcher will have several overlapping sources which will need to be cross referenced in order to improve

confidence in any conclusions drawn (Li et al., 2013). It is unsurprising that many European countries with numerous readily accessible archives have given rise to research projects concerning historical floods; Brázdil et al., (2006) cite numerous European studies spanning no fewer than 10 countries. In China too there is a long history of recording high water marks that have been used in historical flood studies (see for example Li et al., 2013). Information sources include articles or photographs from newspaper archives (MacDonald, 2014), high water marks carved onto bridges or other buildings (MacDonald, 2007), dated stones placed at high water to mark of out of bank flows (Condie and Lee, 1982), diary or journal entries and even literary works (The Bristol Post, 2013).

Regardless of the source, all the data must be subjectively evaluated as to their reliability, accuracy and the benefit they bring to the flood frequency estimates. For example a recording of a single flood event from a journal of 1,000 years ago may provide beneficial insight into the impact of the flood on contemporary society (Brázdil et al., 2006) and assist in the estimation of the Probable Maximum Flood (see for example Acreman, 1989; Kirby and Moss, 1987) for a location, but will be of little value in assisting the estimation of modern day flood frequencies if the source doesn't cover a reasonable contiguous period. If, however, the historical flood record provides some quantitative information on the flood magnitude and covers a contiguous multi-decade period such that the researcher can be reasonably confident that all significant floods in that period at that location are recorded then the data can often be combined with the recent, instrumental time series to improve the estimation of flood frequencies.

It is the estimation of water level (or discharge) that constitutes a 'significant flood' that is key because this becomes the 'perception threshold' ( $Q_0$ ) for the historical time series which can then be treated as a 'censored sample' for statistical purposes (Reis and Stedinger, 2005). Furthermore, even if it is infeasible to estimate the magnitude of the floods above the threshold of perception the historical time series can still be incorporated as a 'binomial-censored' sample whereby it is known that in the historical record of  $n$  years,  $Q_0$  was exceeded  $k$  times (Stedinger and Cohn, 1986). The resulting data set combining a systematic AMAX time series with a historical censored sample

may look something like figure 6.1, note that it is likely that the uncertainty in the peak discharge (not shown in figure 6.1) is likely to be far greater for the historical estimates than the instrumental record and this must be considered when estimating the uncertainty of the flood frequency curve (Viglione et al., 2013).

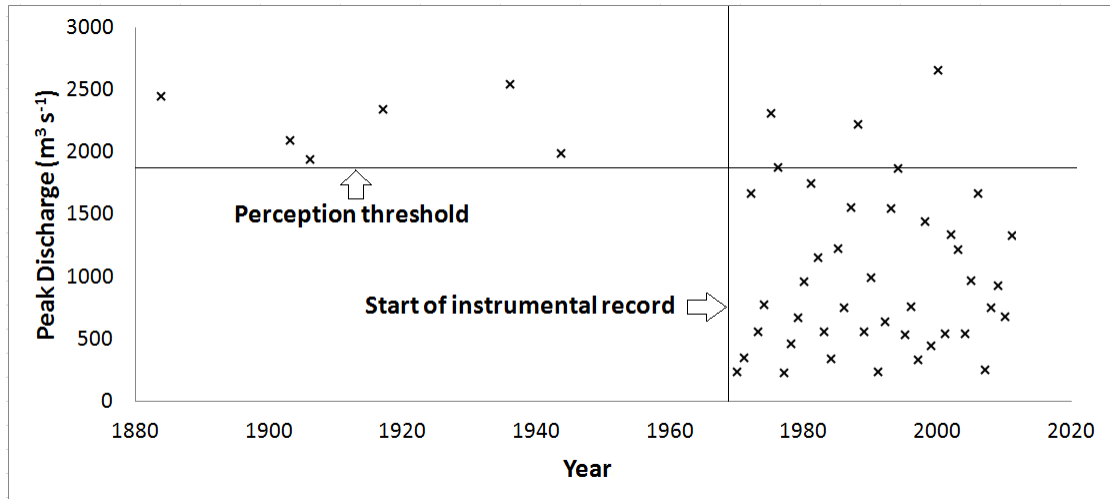


Figure 6.1. Simulated flood record showing AMAX records from systematic instrumental time series starting in 1970, preceded by a historical time series starting in 1880. The ‘perception threshold’ for the historical floods is estimated at  $1,900 \text{ m}^3 \text{ s}^{-1}$ . The uncertainty in peak discharge estimates is not shown.

Methods of using maximum likelihood estimators for parameterising distributions based on censored samples from historical records have been available since the 1940s (Cohen, 1950). As the systematic recording of peak discharges grew, these methods were adapted to work in situations where both censored historic data and a shorter instrumental records were available (Kirby and Moss, 1987). MLE parameterisations were proposed for the commonly used distributions listed in section 6.5.1 (Condie, 1986; Condie and Lee, 1982), as well as new plotting position formulas (Hirsch, 1987). Aware of the limitation of the analytical approaches to account for stochastic errors and bias both in the estimates of discharge and the selection of distribution and fitting methods, researchers were quick to make use of the computers at their disposal to apply Monte Carlo methods for estimating uncertainty (Condie and Lee, 1982; Stedinger and Cohn, 1986) and comparing parameter fitting methods (Cohn et al., 1997; Cohn et al., 2001). The Monte Carlo methods applied can also be used for

generating a full AMAX time series that covers the historical and instrumental periods by 'filling-in' the censored AMAX records from the historical period with copied data from the systematic record that are below the perception threshold (Kidson and Richards, 2005; Kroll and Stedinger, 1996). More recently, Bayesian models have been developed that can combine uncertain estimates of historical and palaeo-flood events with data from systematic gauge records (examples include O'Connell et al., 2002; Parent and Bernier, 2003; Reis and Stedinger, 2005; Viglione et al., 2013), and this is the approach taken in chapter 7 for deriving the flood frequency curve in Carlisle.

## 6.8 Uncertainty in flood frequency analysis

In the review of flood frequency analysis so far, some of the many sources of uncertainty have been alluded to, such as the limited data on peak flows and the errors in measurements of those flows. Whilst a comprehensive review of all sources of uncertainty in flood risk is beyond the scope of this thesis, it is necessary for researchers to acknowledge as many as possible even if they are not all explicitly quantified in the research that follows. More detailed analysis of uncertainty in flood risk can be found in works such as Beven and Hall (2014).

### 6.8.1 Insufficiently long AMAX record

As already discussed, sampling error due to the unavailability of a sufficiently long time series of extreme discharge measurements is an important source of uncertainty in flood frequency analysis. A study by Apel et al. (2008) examining the contribution various sources of uncertainty to flood hazard find the length of the AMAX data series to be one of the dominant sources of uncertainty in flood hazard estimation.

When performing a single site analysis of discharge data to derive the flood frequency curve at a location, the uncertainty due to the length of the AMAX data series can be quantified relatively simply by re-sampling of the data (Kjeldsen et al., 2014a). An example of this is given in chapter 7.

### 6.8.2 Model error

In flood frequency analysis the model error refers to the uncertainty introduced by the choice of the EVD used to model the data (Wood and Rodríguez-Iturbe, 1975). No matter how many parameters the distribution has, in reality the AMAX time series is

not bound to converge on any particular mathematically defined distribution or even a combination of several distributions.

### 6.8.3 Parameter fitting method

The methods described in section 6.5.2 will tend to produce differing estimates of the EVD parameters leading to uncertainty in the flood frequency curve. This source of error is not usually considered as it tends to be masked by the large model and sampling uncertainties (Cunnane, 1987).

### 6.8.4 Errors in discharge estimates

The AMAX time series data used in the derivation of flood frequency curves are typically taken from on-site gauge readings of discharge typically using a rating curve (Shao et al., 2014), so will have the accuracy of the gauge readings as an absolute limitation, possibly with other, larger errors in practice (Di Baldassarre and Montanari, 2010; Shao et al., 2014). Estimates of the accuracy of within bank discharge figures based on a rating curve vary widely, Pappenbeger et al. quote figures of up to 8.5% with 6% being typical and this is similar to the results of more recent research by Birgand et al (2013) and Domeneghetti et al. (2012a). However Di Baldassarre and Montanari (2010) find average errors of 25.6% when considering additional sources of uncertainty such as seasonal variation in channel roughness. Even in Di Baldassarre and Montanari's research the channel geometry is considered stationary (beyond seasonal variation), whereas in reality, the uncertainty in the stage discharge relationship increases with the time since the on-site gauge readings (Jalbert et al., 2011). What's more, gauge readings are known to be least reliable when the river is out of bank (Brakenridge et al., 1998) unfortunately this is when they are going to have the greatest impact on the final derivation of the flood frequency curve. The wide range of possible errors in the discharge estimates implies that it is unwise to use consistent confidence limits in the discharge limits across multiple gauges. The reliability of individual gauges from which the data has come should be considered subjectively when quantifying the uncertainty in discharge figures (Le Coz et al., 2014).

Estimates of discharge during historical and palaeo-floods will tend to be far less certain than peak discharge of floods from systematic gauge readings. The accuracy



and reliability of the sources from which the discharge estimates are taken should be carefully considered and it may be that historic flood discharge estimates should be represented by a uniform distribution between upper and lower limits (e.g. Viglione et al., 2013) or just as binomial data whereby it can only be said that the flood was above a certain magnitude (Stedinger and Cohn, 1986).

#### 6.8.5 Non-stationarity

The methods underlying extreme value statistics are often predicated on assumptions of stationarity in the observed variable (Khaliq et al., 2006; Koutsoyiannis and Montanari, 2007). For example, the assertion made by Fisher and Tippett (1928) that the asymptotic distribution for the largest value in a block of  $n$  values will be of a generalised extreme value type as  $n$  tends to infinity is based on the data being a sequence of independent, identically distributed (iid) random variables. The condition that the data is 'identically distributed' will be violated if there are any trends or long term variability in the time series and there is a growing body of evidence for the existence of trends in natural processes (Cohn and Lins, 2005; Milly et al., 2008). In flood frequency analysis there are several possible drivers of non-stationarity:

- **Natural climate variability.** Flood frequency estimations may be affected by multi-decadal scale natural climate cycles attributed to factors such as variation in solar output, volcanic eruptions and variations in ocean circulation (Bell and Walker, 2005; Koutsoyiannis, 2003). Studies in the UK and elsewhere have identified historic 'flood-rich and flood-poor' periods (examples include Barriendos Vallve and Martin-Vide, 1998; Bayliss and Reed, 2001; Benito et al., 2004; Benito et al., 2008; Boe and Habets, 2014; Kiem et al., 2003; Robson, 2002; Zheng et al., 2006). The influence of the North Atlantic Oscillation (NAO) in particular has been shown to have a strong influence on the frequency and magnitude of UK and European floods (Burt and Howden, 2013; Salgueiro et al., 2013; Silva et al., 2012). This suggestion is backed up by some specific research into flood-rich periods in Cumbria, UK by Pattinson and Lane (2011) who find evidence that cycles in the North Atlantic climate system are correlated with variations in flood frequencies in Cumbria.

A specific stationarity issue for the UK is the suggestion that there was a 'flood poor' period in the middle of 20<sup>th</sup> century (Shaw et al., 2010) and during this period, in the 1960's, the majority of the river gauging stations were installed due to the Water Resources Act 1963 (Bayliss and Reed, 2001). If it is the case that the UK experienced a period of overall reduced flooding in the decades prior to 1990 the effect of this would be an exaggeration of the return periods of floods recorded in the last 2 decades which would not necessarily be ameliorated by the use of regional frequency analysis since many of the gauge records cover the same period.

- **Natural or anthropogenic climate change.** It has been established that the likelihood of flooding is sensitive to small changes in climate (Benito et al., 2004; Hunt, 2002). So any long term change in the climate over the next century is likely to have a significant effect on river flows in the UK (Arnell et al., 2014; Fowler and Kilsby, 2007). Indeed, there is already evidence of the impact of climate change on national hydrology in the UK (Kay et al., 2011; Pall et al., 2011) and beyond (Alfieri et al., 2015; Coumou and Rahmstorf, 2012; Min et al., 2011), although, as with many studies on the impacts of anthropogenic climate change, there is some dispute about distinguishing the signal from the noise (Arheimer and Lindström 2014; Beven, 2011; Hannaford and Buys, 2012).

In the UK, a simple approach to dealing with the risk of climate change increasing the peak flood flows over the next century, suggested by the Environment Agency (2005) and adopted by the Department for Environment, Food and Rural Affairs (Defra) is to recommend an allowance of an additional 20% on top of peak river flows to account for climate change up to 2080 (DEFRA, 2006). This was considered the best approach based on UK climate impact research (UKCIP02) (Hulme et al., 2002) prior to the more detailed impact assessment (UKCP09) (Murphy et al., 2009) which enables a less 'catch all' approach for modelling the effects of climate change on flood frequency and severity (Kay and Jones, 2012).

- **Land use change in the catchment.** The impact of changes within a catchment on the likelihood and severity of flooding has been a subject of

research for over 50 years (Blöschl et al., 2007; Lane et al., 2007; O'Connell et al., 2007). The nature of the change in question may either exacerbate or attenuate the problem of flooding. Deforestation and urbanisation without consideration of sustainable drainage can both result in rapid and increased run-off (De Roo et al., 2001; Gilroy and McCuen, 2011; Wisner et al., 2004). On the other hand the construction of dams and reservoirs tend to reduce the extent of the response of the catchment downstream and can form part of a flood mitigation scheme (De Roo et al., 2003).

The extent and rapidity of anthropogenic changes in many parts of the world is extreme (He et al., 2013, in press) but it is not necessarily feasible to assess the impact of those changes on flood risk where the, possibly chaotic, signal of the relationship between land use and flooding needs to be discerned against a backdrop of climatic change and variability (Pattison and Lane, 2012). A problem that tends to become more intractable with increasing catchment size (Blöschl et al., 2007). For the case of the River Eden catchment in Cumbria, although the conurbation of Carlisle itself has expanded significantly over the last century, overall the catchment is still relatively undeveloped with less than 1% urbanised suggesting catchment urbanisation can be discounted as a significant source of change in flood frequency (Pattison and Lane, 2011).

- **River channel geometry and floodplain storage.** A combination of natural (Sutcliffe, 1987) and man-made alterations to the channel can have a significant effect on extent and consequences of a flood even if the peak discharge is unaffected (Neppel et al., 2010; Shaw et al., 2010). For example, if a river channel is widened through a dredging operation in an area of flood risk, the purpose of this will typically be to allow a greater discharge through the channel before the flow goes out of bank (Pattison and Lane, 2012). In terms of the peak discharge, this change will have no effect on the flood frequency curve at the site of interest, but it could have a huge impact on the perception of the severity of an event, so needs to be considered when estimating the severity of historical floods that exceeded the 'threshold of perception' (see figure 6.1) prior to systematic gauging records.

Conversely there are plenty of channel changes that will alter the peak discharge at the flood risk site. For example, the construction of levees upstream of the site of interest will reduce the upstream floodplain storage meaning water is channelled downstream at a greater rate (Pattison and Lane, 2012). Similarly, the construction of bridges which reduce the channel width and constrict floodplain flow will have the effect of lowering the peak discharge through the site of interest but will increase the likelihood and extent of out of bank flows due to the backwatering effect of the downstream obstacle. These effects were modelled for a stretch of the River Cherwell, Oxfordshire, UK by Acreman et al. (2003) who used historical maps to simulate the pre-engineered channel geometry which had improved upstream floodplain connectivity and found that downstream peak discharge was reduced by 10-15%. A similar effect of downstream conveyance reduction was found by Borman et al. (1999) when simulating the reintroduction of meanders upstream where the channel had previously been straightened.

Taking account of trends and non-stationarity in a flood frequency model complicates the process of designing a flood frequency model for a site especially if that model is to incorporate data from multiple sources (Cunderlik and Burn, 2003; Serinaldi and Kilsby, 2015). Reynard et al. (2006b) describe Bayesian frameworks that can incorporate linear trends and step changes in the underlying processes, and some models using non-stationary parameters are proving useful for quantifying the changes in flood risk (Lima et al., 2015; Lopez and Frances, 2013; Villarini et al., 2009). It may be possible to account for the effects of channel and floodplain changes at the site with the use of hydraulic models using a DEM that reflects the historic channel and floodplain topography (Naulet et al., 2005; Sheffer et al., 2003), this is the approach taken in chapter 7.

## Chapter 7. Estimating flood frequencies in Carlisle

### 7.1 Introduction

In this chapter the flood frequency curve is generated for the River Eden, Carlisle, Cumbria, UK at the location of the Sheepmount river gauge (CEH, 2014). The method employed will make use, not only of the 46 years of data from the Sheepmount river gauge, but also historical flood information from Carlisle. This resulting flood frequency curve will have narrower confidence limits than those if solely the gauge data was used. The purpose is firstly to estimate the range and uncertainty in the recurrence interval for the January, 2005 flood, whose peak discharge has been estimated to be between  $1490 \text{ m}^3\text{s}^{-1}$  (Horritt et al., 2010) and  $1600 \text{ m}^3\text{s}^{-1}$  (Fewtrell et al., 2011b) and is recorded as  $1516 \text{ m}^3\text{s}^{-1}$  in the National River Flow Archive (CEH, 2014). The flood frequency curve will also allow ranges to be estimated for the peak discharge of the various ‘design floods’ that play important roles in policy making and flood management. For example the extent of the 0.01 annual exceedance probability (AEP) fluvial flood, formerly known as ‘the hundred year flood’, is used to define the areas throughout the country defined as ‘high risk of flooding’ by the Environment Agency (2011d).

The chapter is structured as follows: first, in section 7.2 the recommended methods of flood frequency estimation in the UK are reviewed and flood frequency curves for the Sheepmount gauge data are plotted. Next the nature of the historical flood data for Carlisle is summarised in section 7.3. Section 7.4 then introduces the concept of Bayesian inference followed by Section 7.5, which describes the Bayesian model that has been developed to derive the flood frequency curve for Carlisle. Section 7.5 forms the core of the chapter. It details the model structure and parameters which is followed by a sensitivity analysis and a discussion of the model results. Section 7.6 concludes the chapter.

### 7.2 Flood frequency estimation in Carlisle using gauged data

Scientists and practitioners have been estimating flood frequencies for many decades. In the UK the Flood Studies Report (FSR) (NERC, 1975), prescribed

standardised ways to estimate flood frequencies from the available river and rainfall gauge data using the statistics of extreme values developed in the first half of the twentieth century (Daniels, 1982). As is often the case when attempting to model naturally occurring extreme events, the available data is limited and subjective choices need to be taken on the methods used to make best use of the available data. The Flood Estimation Handbook (FEH), the successor to the FSR (IH, 1999) describes several ways of estimating flood frequency curves which, together with the related WINFAP-FEH software from WHS (2014) are heavily recommended by the Environment Agency (2012). The WINFAP-FEH software makes it relatively simple to derive a flood frequency curve for a river location, especially if there is an operational river flow gauge at that location; however as this section shows the different methods available in the WINFAP-FEH software may provide inconsistent results. In the following sections flood frequency curves for the River Eden at the Sheepmount river gauge are derived using the WINFAP-FEH software.

#### 7.2.1 Single site analysis

Figure 7.1 shows flood frequency curves generated by the WINFAP-FEH software using just the 46 years of annual maximum discharge time series data (section 2.7) from the Sheepmount river gauge. The flood frequency curves are fitted to the data using the method of L-moments (Hosking, 1990) described in section 6.5.2. Figure 7.1 shows three different extreme value distributions (generalised logistic (GL), generalised extreme value (GEV) and log-Pearson Type III (LP3)) fitted to the data as well as 95% confidence intervals for the GEV distribution (section 6.5.1). These confidence intervals were calculated by the WINFAP-FEH software using a balanced re-sampling method (WHS, 2009a), which is a type of commonly used ‘bootstrap’ procedure (Kjeldsen et al., 2014a). The confidence intervals represent the uncertainty of the curve fitting due to the length of the time series: the longer the time series, the narrower the confidence interval would be. Unfortunately, long and reliable time series of AMAX records for river gauges are uncommon in the UK; the 46 years recorded at Sheepmount is comparatively long, the average record length being roughly 35 years (Kjeldsen et al., 2008).

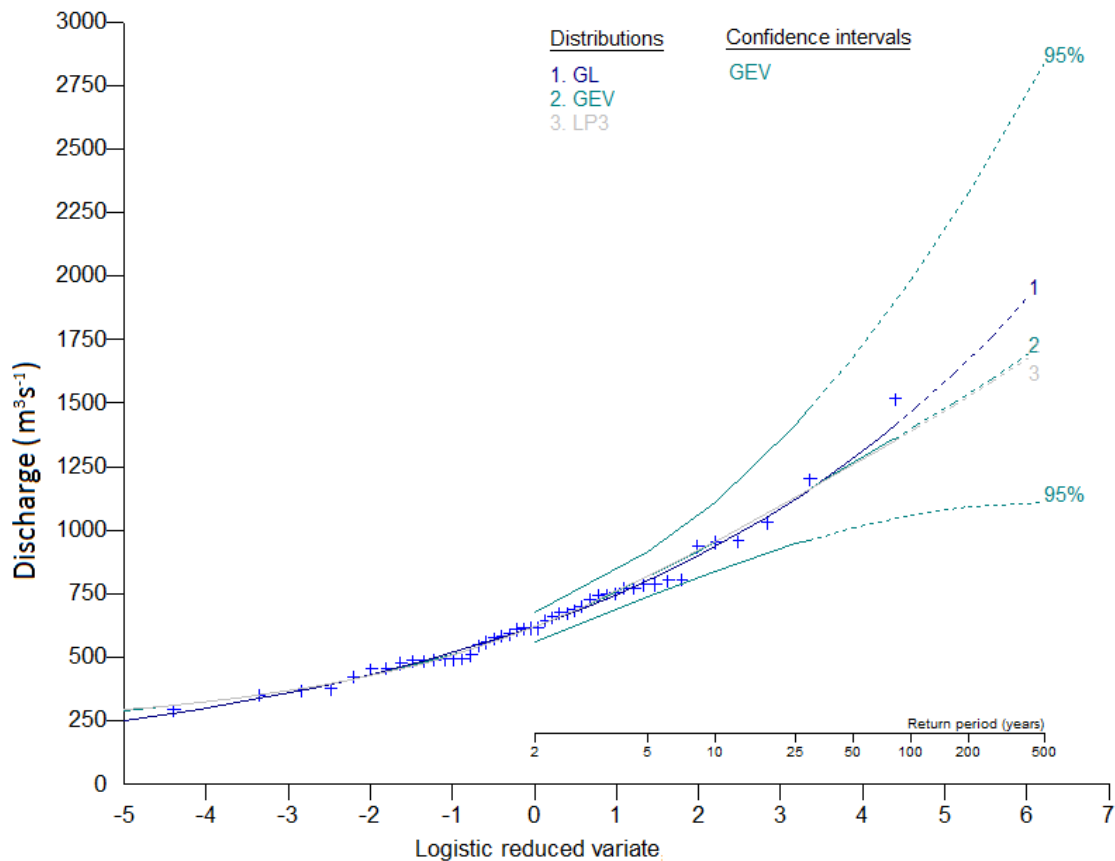


Figure 7.1 Flood frequency curve generated using single site analysis and showing annual maxima (AMAX) discharge data for the River Eden at the Sheepmount river gauge, plotted using WINFAP-FEH software from WHS (2009a). Three different extreme value distributions (EVDs) have been fitted using the method of L-moments: 1. Generalised Logistic (GL); 2. Generalised Extreme Value (GEV); 3. Log-Pearson Type III (LP3). Also shown are 95% confidence limits for the fitted GEV curve based on balanced re-sampling (4,999 samples) taken from the AMAX series. The data points from the AMAX data series are plotted using the Gringorten plotting position formula (Gringorten, 1963).

Figure 7.1 shows 3 different distributions all fitted to the same data using the method of L-moments (section 6.5.2). The different distributions match each other closely until the higher return periods are reached when the GL distribution diverges from the other 2. Indeed it is a feature that there is often very little to choose between different distributions fitted within the range of the data, but when extrapolating beyond the range of the data the distributions diverge considerably (Keef, 2014). In this case the GEV and LP3 distributions match very closely for all return periods shown.

Overall the difference due to choice of commonly used extreme value distributions is small compared to the uncertainty from the due to the length of AMAX time series. The method used to fit the curve to the data (L-Moments, L-Median, Maximum Likelihood) shows still less variation than the choice of EVD (see table 7.1). The median and 95% confidence limits for three EVDs estimated from single site analysis are shown given in table 7.1 for the design floods at Carlisle. The estimated AEP for the peak discharge ( $1516 \text{ m}^3\text{s}^{-1}$ ) measured during the January, 2005 flood using the GL distribution fitted with the method of L-Moments is 0.0055 (return period of 180 years), with 95% confidence intervals 0.0386 to less than 0.0001 (return periods 34 to greater than 10,000 years).

Table 7.1. Single site estimates for various EVDs and fitting techniques of the discharge at the Sheepmount gauging station for certain design floods with 95% confidence intervals.

<b>AEP</b>	<b>0.5</b>	<b>0.0133</b>	<b>0.01</b>	<b>0.001</b>
<b>(return period, years)</b>	<b>(2)</b>	<b>(75)</b>	<b>(100)</b>	<b>(1,000)</b>
<b>EVD (Fitting Technique)</b>	<b>Mean Discharge (<math>\text{m}^3\text{s}^{-1}</math>)</b>			
	<b>(95% confidence interval)</b>			
<b>GL (L-Moments)</b>	621	1386	1464	2267
	(563 - 682)	(1086-1887)	(1124-2046)	(1394-4056)
<b>GL (L-Median)</b>	615	1374	1452	2247
	(615-615)	(1076-1876)	(1109-2036)	(1381 – 4062)
<b>GEV (L-Moments)</b>	617	1342	1400	1876
	(558-678)	(1036-1853)	(1056-1983)	(1123-3295)
<b>GEV (L-Median)</b>	615	1339	1396	1871
	(615-615)	(1028-1864)	(1042-1996)	(1095-3320)
<b>GEV</b>	619	1329	1384	1838
<b>(Maximum Likelihood)</b>	(559-680)	(994-1815)	(1008-1940)	(1023-3125)
<b>LP3</b>	618	1335	1391	1712
<b>(Moments)</b>	(561-679)	(1046-1786)	(1071-1899)	(1191-2618)



### 7.2.2 Pooled analysis

To overcome the problem of estimating long return period flood frequencies with short AMAX time series and reducing the uncertainty in the flood frequency curve, the Flood Estimation Handbook recommends using pooled analysis, also known as regional frequency analysis (IH, 1999; Kjeldsen et al., 2014a). This method takes AMAX time series from a pool of catchments with similar hydrological properties to the target catchment. The WINFAP-FEH software facilitates this process with its 'pooled analysis' feature that implements the algorithms for selecting the pooling group and a goodness of fit test (WHS, 2009a). Figure 7.2 shows the flood frequency curve using a pooling group (details in table 7.2). The flood frequency curve is calculated using a weighted average of the individual single site growth curves (see section 6.6) which are then weighted according to the similarity of the catchments to the target catchment (Kjeldsen et al., 2008). In this way the pooling group method can be referred to as 'enhanced single site analysis' since the AMAX time series of the target site is given the greatest weighting (WHS, 2009b).

The logic behind the use of a pooling group method is that the inclusion of more data points from which to estimate the flood frequency curve will result in much lower sampling uncertainty (Kjeldsen et al., 2014a). The WINFAP-FEH software recommends constructing pooling group sizes to give at least 500 'virtual' years of AMAX data – considerably longer than any AMAX time series from a single river gauge in the UK. However the inclusion of data from other gauging stations means the time series departs from the ideal of being independent and identically distributed, the effect of which will be to, at least partially, negate the reduction in uncertainty. The example below shows evidence of strong correlation between some of the sites selected for the pooling group of the Sheepmount gauging station.

Details of the pooling group selected by the WINFAP-FEH software for the Sheepmount gauging station are shown in table 7.2. Using the pooling group shown in table 7.2, the estimated AEP for the peak discharge ( $1516 \text{ m}^3\text{s}^{-1}$ ) recorded during the January, 2005 event is 0.00559 (return period of 179 years) and 0.00294 (return period of 340 years) for the GL and GEV distributions respectively both fitted using the technique of L-Moments. Note that the software has selected data from 3 river gauges

on the River Spey, indeed the Spey at Arbelour and Spey at Boat o Brig are only a few kilometres apart (see figure 7.3). The catchment overlap for these gauges would result in a very strong cross-correlation as can be seen in figure 7.4 where the AMAX figures for the three gauges on the River Spey are plotted next to each other.

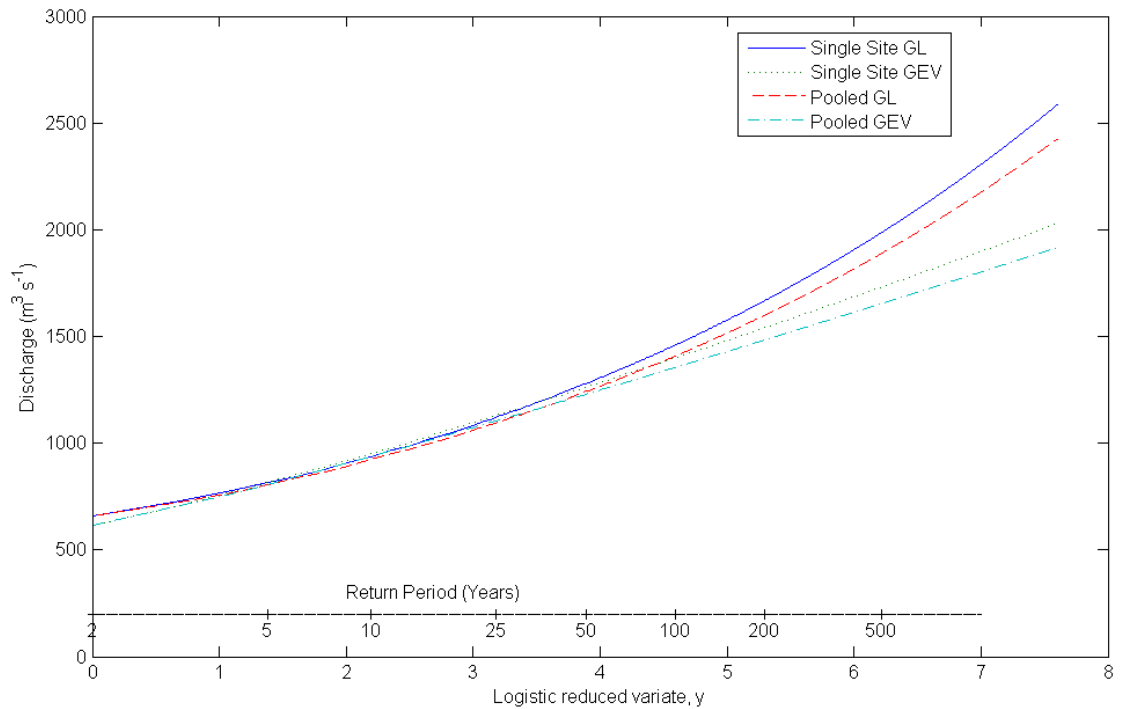


Figure 7.2. Flood frequency curves generated using pooled (enhanced single site) and single site analysis of the WINFAP-FEH software for the River Eden at the Sheepmount river gauge. 2 extreme value distributions (EVDs) have been fitted using the method of L-moments: 1. Generalised Logistic (GL); 2. Generalised Extreme Value (GEV).

A correlation analysis by the Institute of Hydrology calculated the Spearman's rank correlation between the AMAX times series of all pairs of gauges across the UK (IH, 1999). A decaying exponential model was fitted to the data giving the correlation between sites to be  $\exp(-0.016d)$  where  $d$  is the distance (in km) between the gauging sites (Kjeldsen and Jones, 2007). This cross-correlation effectively reduces the amount the pooling group informs the flood frequency curve and consequently results in an increase in uncertainty (Kjeldsen and Jones, 2006). Furthermore, a generalisation of this specific point can be made because all the pooling group catchments are selected only from the UK and the AMAX time series usually start at some point in the second half of the twentieth century. Pattinson and Lane (2011) present evidence that the UK

has undergone flood-rich and flood-poor periods in the past 2 centuries, and this will have the effect of further undermining the goal of pooled site analysis to ‘substitute space for time’ (Van Gelder et al., 2001). O’Brien and Burn (2014) address this issue of non-stationarity for pooling groups in Canada.

Table 7.2 Pooling group details for the River Eden at Sheepmount. The total number of years of record is 518.

<b>Station</b>	<b>Distance  (“parameter space”)</b>	<b>Gauged record length (years)</b>	<b>QMED (m<sup>3</sup>s<sup>-1</sup>)</b>	<b>Area (km<sup>2</sup>)</b>
<b>Eden @ Sheepmount</b>	0.000	46	615.487	2276
<b>Severn @ Montford</b>	0.266	59	292.410	2027
<b>Wye @ Belmont</b>	0.274	104	388.880	1894
<b>Mourne @ Drumnabuoy House</b>	0.343	30	599.924	1844
<b>Spey @ Aberlour</b>	0.343	65	415.619	2645
<b>Tyne @ Bywell</b>	0.403	56	876.427	2172
<b>Spey @ Boat o Brig</b>	0.418	54	478.527	2852
<b>Clyde @ Blairston</b>	0.435	50	376.239	1699
<b>Spey @ Grantown</b>	0.450	54	227.227	1746

The issues of correlation and heterogeneity mean that calculating confidence intervals for the flood frequency curves generated using pooled analysis is not as simple as the case for single site analysis. Hosking and Wallis (1997) explain a relatively simple Monte Carlo simulation approach which becomes more complex when inter-site correlation is considered. Kjeldsen and Jones (2006) suggest the use of asymptotic theory to approximate the variance of quantile estimates which was then updated to be consistent with the subsequent changes to the pooling group method (Kjeldsen et al., 2008) and used to give confidence limits to AEP estimates of extreme floods that occurred across Cumbria in November, 2009 (Miller et al., 2012). However, at present, no method is implemented by the WINFAP-FEH software.

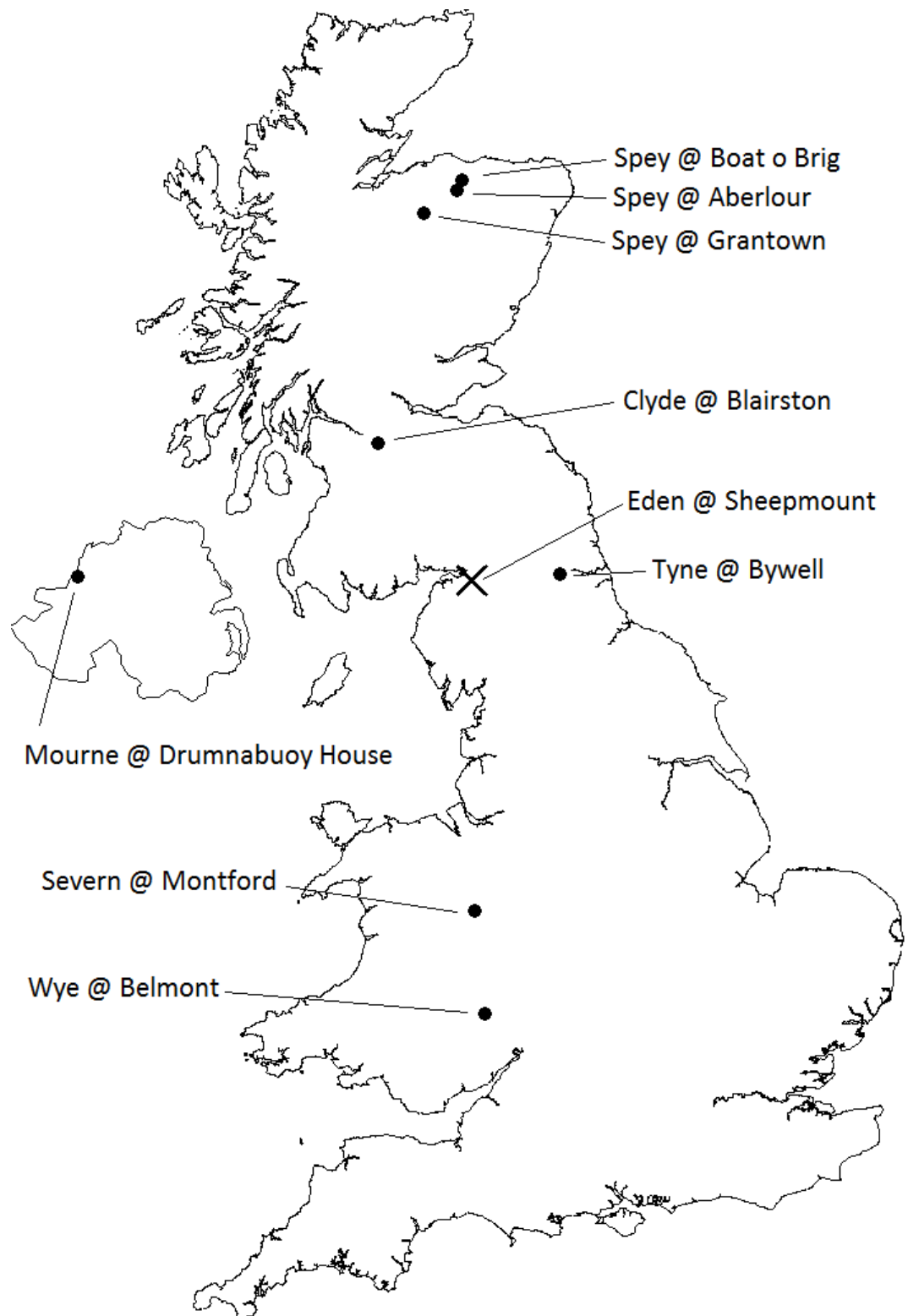


Figure 7.3. Locations of river gauging stations in the pooling group selected for the River Eden at Sheepmount flood frequency analysis.

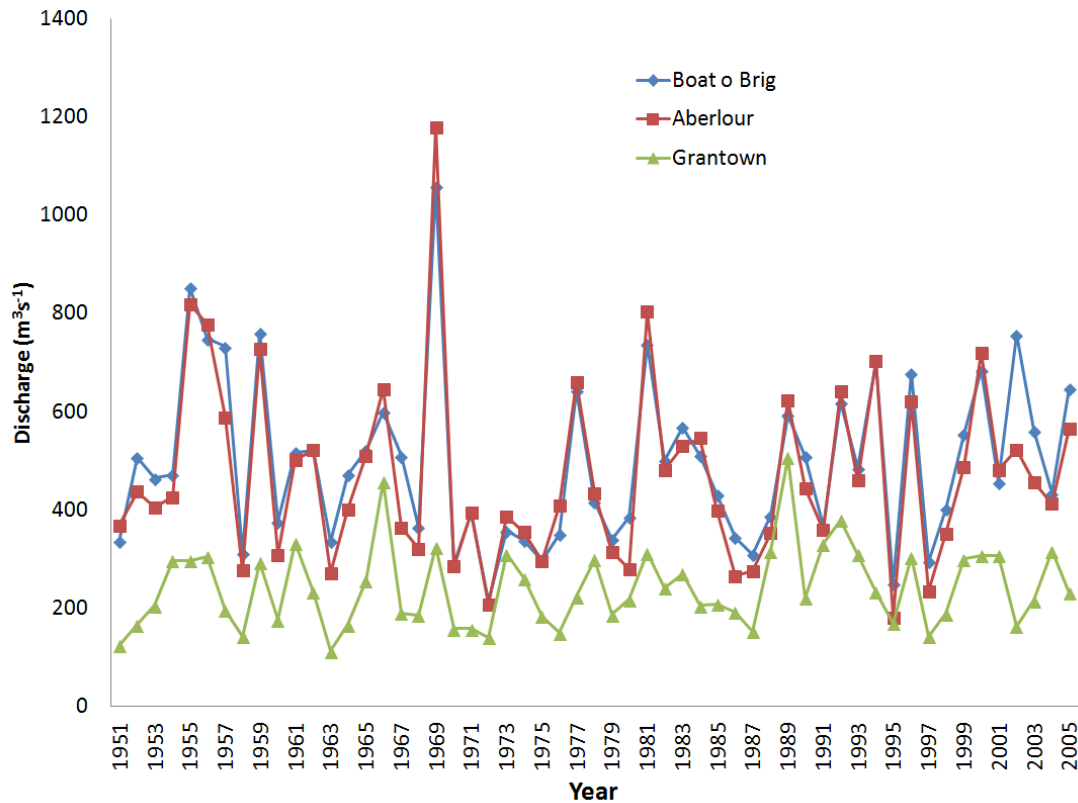


Figure 7.4. AMAX discharge figures for the 3 gauging stations on the River Spey that are included in the pooled analysis for the flood frequency curve of the River Eden at Sheepmount.

Whilst the WINFAP-FEH software and the various methods of flood frequency estimation implemented within it are recommended for use by Environment Agency staff when carrying out flood estimations, it would be wrong to say that the recommendation is to follow the procedures ‘blindly’ with no consideration of the inadequacies of the methods (Environment Agency, 2012). The flood estimation guidelines document offers several pages of advice on which method may be most appropriate and ways to manipulate the pooling group using local knowledge of the site of interest for best results (Environment Agency, 2012). There is plenty of anecdotal evidence of a healthy scepticism of WINFAP-FEH method amongst hydrologists (British Hydrological Society group on LinkedIn, 2014).

### 7.2.3 Uncertainty in gauged data

Discharge readings from river flow gauges are often inferred from measurements of water level (stage) by means of a rating curve (Shaw et al., 2010). The rating curve is typically a power-law function of the form (Di Baldassarre et al., 2012):

$$Q = a(h - b)^c \quad (7.1)$$

Where  $Q$  is the discharge,  $h$  is the stage (water level) and  $a$ ,  $b$  and  $c$  are parameters that are calculated empirically from a series of gaugings, which are more direct measurements of flow at the site (Shaw et al., 2010). Often, the stage-discharge relationship changes substantially as the stage increases in which case more than one power-law function is required. The accuracy of the discharge estimates from river gauges varies considerably with the type of gauge, the geomorphology of the channel and the level of water: uncertainty in discharge is likely to be greater at times of flood (Di Baldassarre and Montanari, 2010; IH, 1999; Neppel et al., 2010; Rosso, 1985).

Estimates of the general errors in discharge estimates range from 3-5% of the discharge estimate (Cong and Xu, 1987) up to as much as 30% for extreme flows (Kuczera, 1996; Potter and Walker, 1981). Other sources give typical values in the range of 4% to 8% with a large number around 6% (see for example Leonard et al., 2000; and sources therein).

The gauge on the River Eden at Sheepmount is listed as 'grade B' from the Flood Studies report (CEH, 2014). In a Flow Quality Comment document, the general comment on the rating curve in use at Sheepmount is that gauging shows less than 10% deviation from the rating, and the high flow record is "good to valid" although substantial bypass flow is noted when the level is above bank (Environment Agency, 2011f). In a paper modelling the January, 2005 Carlisle flood, Horritt et al. (2010) set up a simple finite volume (SVF) model (Horritt, 2004) in order to assess the performance of the Sheepmount gauge and the Cummersdale gauge on the River Caldew. They find the EA rating curve to be a good fit to both the within bank stage-discharge measurements (up to  $1000 \text{ m}^3\text{s}^{-1}$ ) and for the January, 2005 event, although they recommend revising the peak flow from 1520 down to  $1490 \text{ m}^3\text{s}^{-1}$ . This is a significant finding when considering the flood frequency curve at a site, because, as is

demonstrated by Miller et al. (2012) the largest value in an AMAX time series can have a dramatic impact on the flood frequency curve.

For the purposes of estimating the flood frequency curve for the River Eden at Sheepmount, the literature reviewed in this section suggests that the errors in the gauge readings for the AMAX time series must be accounted for, but can be relied upon to be within approximately  $\pm 10\%$  even for the out of bank events. The Bayesian model described in section 7.5 includes this gauge uncertainty and the sensitivity of the model to this uncertainty can be seen in figure 7.5.

#### 7.2.4 Recommendations to practitioners

The issues highlighted above hint at the complexities and uncertainties of performing a flood frequency analysis even for a site with a reliable gauge record several decades long. The Environment Agency's guidelines for managers of flood estimation studies (2012) acknowledge the complexity of the problem and echo the Flood Estimation Handbook's recommendation to allow up to 50 days for a thorough flood estimation study (IH, 1999).

The use of historical flood data has been recommended as a valuable data source for improving the reliability of estimates of longer return period floods (IH, 1999). Bayliss and Reed (2001) provide guidance on how practitioners may incorporate historical records of floods in the UK their flood estimations. But without the convenience of a pre-packaged software solution for incorporating historical data, the use of historical flood data is uncommon (Kjeldsen et al., 2014b). Furthermore, many of the proposed methods for incorporating the historical flood data do not consider the uncertainty in the discharge estimates of historical events (e.g. MacDonald et al., 2013), which given their nature are likely to be far more uncertain than the gauged records.

### 7.3 Historical data at Carlisle

Historical records of floods can come from a variety of sources such as epigraphic markings inscribed on walls (MacDonald, 2007), reports in newspapers and journals (MacDonald, 2014) or (un)official local chronicles (Brázdil et al., 2006; Elleder, 2015). The question of the reliability of the historic records is an important one. An epigraphic mark or a description in a journal can give an idea of the maximum flood depth at a certain point, and some method must be derived to turn this into an estimate of the peak discharge of the flood, usually a rating curve (see section 7.2.3). These estimates of historic flood discharge are likely to contain considerable errors: the reliability of the source must be considered; geomorphological changes to the channel mean the current rating curve equation is less applicable to historic floods (see for example Archer et al., 2007a). However, even inaccurate historic flood data can provide valuable information for flood frequency assessment (Kjeldsen et al., 2014b).

In Carlisle itself flood marks have been recorded on the Eden Bridge since its construction in 1815, and these can be cross referenced with newspaper reports and a staff gauge maintained by Carlisle City Council for nearly 100 years from 1850 (Environment Agency, 2006). Records of historic flood events in Carlisle between 1800 and 1970 have been collated in Smith and Tobin (1979) with an updated version in the Cumbria Floods Technical Report (Environment Agency, 2006) produced as a response to the 2005 floods. Table 7.3 summarises data for the 212 years from 1800 to 2012.



Table 7.3. Extreme historical and gauged flood data for Carlisle since 1800. Sources: Cumbria Floods Technical Report (Environment Agency, 2006) ; Smith and Tobin (1979); Environment Agency Sheepmount Gauging Station records (CEH, 2014); Carlisle Encyclopaedia references from local newspapers (Carlisle History, 2014).

<b>Date</b>	<b>Estimated level at Eden Bridge (m AOD)</b>	<b>Estimated level at Sheepmount station (m AOD)</b>	<b>Estimated discharge at Sheepmount station (m<sup>3</sup> s<sup>-1</sup>)*</b>	<b>Approx. Rank</b>	<b>Notes</b>
<b>2/1809</b>	13.6 – 14.0	12.7	1025	7 - 11	1
<b>9/1809</b>	13.6	12.5		12 - 18	1,4
<b>11/1815</b>	13.6	12.5	963	12 - 18	1
<b>2/2/1822</b>	14.00	12.9	1089	2 - 6	2
<b>1/1/1851</b>	13.41	12.3	905	25 - 31	2
<b>10/2/1852</b>	13.53	12.5	941	7 - 11	2
<b>13/12/1852</b>	13.83	12.7	1035	19 - 24	2
<b>8/12/1856</b>	14.19	13.1	1152	2 - 6	2
<b>11/1857</b>	13.45	12.4		25-31	2,4
<b>11/1857</b>	13.55	12.5	947	19 - 24	2
<b>1/2/1868</b>	13.60	12.5	963	12 - 18	2
<b>7/10/1874</b>	13.83	12.7	1035	7 - 11	2
<b>1891</b>	13.42	12.3	908	25 - 31	2
<b>1899</b>	13.6	12.5	963	12 - 18	1
<b>27/1/1903</b>	13.50	12.4	932	19 - 24	2
<b>2/1/1916</b>	13.37	12.3	893	25 - 31	2
<b>27/12/1924</b>	13.63	12.5		12-18	2,4
<b>30/12/1924</b>	13.78	12.7	1019	7 - 11	2
<b>2/1/1925</b>	14.11	13.0	1125	2 - 6	2
<b>21/8/1928</b>	13.45	12.35	917	25 - 31	2
<b>29/12/1929</b>	13.50	12.4	932	19 - 24	2
<b>4/11/1931</b>	14.08	13.0	1116	2 - 6	2
<b>18/10/1954</b>	13.56	12.8	950	19 - 24	2
<b>9/12/1964</b>	13.40	12.3	902	25 - 31	2
<b>17/10/1967</b>		12.28		25 - 31	3,4
<b>23/3/1968</b>		13.16	1200	2 - 6	3
<b>4/1/1982</b>		12.50	957	12 - 18	3
<b>21/12/1985</b>		12.43	936	19 - 24	3
<b>1/2/1995</b>		12.49	953	12 - 18	3
<b>8/1/2005</b>		14.15	1516	1	3
<b>20/11/2009</b>		12.74	1029	7 - 11	3

## Notes:

1. Derived from recurrence interval in Smith and Tobin (1979). For historical records, the water level at the Sheepmount gauging station is calculated as approximately 1.1 m lower than the estimated level at the Eden Bridge.
2. From Cumbria Floods Technical Report (Environment Agency, 2006). For historical records, the water level at the Sheepmount gauging station is calculated as approximately 1.1 m lower than the estimated level at the Eden Bridge.
3. From Sheepmount river gauge records (CEH, 2014).
4. These records not used in historical data set because they are not the maximum flood in for the year.

\* The discharge ( $Q$ ) at the Sheepmount gauging station is calculated from the stage (water level) using the current rating equation (CEH, 2014):

$$Q = 56.612 * (h - 2.980)^{1.699} \quad (7.2)$$

Where  $h$  is the measured (or estimated) stage, which for this site is AOD – 6.9 m.

The historical (pre-gauge) flood data available for Carlisle is in the form of a “censored” time series where discharge estimates for all floods above a certain “perception threshold” are assumed to be known (Stedinger and Cohn, 1986). Combining the gauged data from the Sheepmount gauge (figure 2.8) with the historical estimates (table 7.3) the time series would look something like figure 7.5. Figure 7.5 (a) displays the gauged and historical flood peaks as known values, whereas in reality both the gauged AMAX readings and the historical estimates are uncertain (although the gauges readings are likely to be more accurate than the historical estimates). The ‘perception threshold’ is inferred from the lowest historical flood peak. It is assumed that all floods above the perception threshold that have occurred in Carlisle since 1800 are included in the historical record. The smallest flood in the historical record is estimated to be  $893 \text{ m}^3\text{s}^{-1}$ , suggesting a perception threshold of approximately  $890 \text{ m}^3\text{s}^{-1}$ . Since the perception threshold is inferred from the highly uncertain historical flood record, it will also have an uncertain value. Figure 7.5 (b) shows the uncertainty associated with the gauge readings, historical flood estimates and the perception threshold. It is desirable that the method used to derive the flood frequency curve should incorporate all these sources of uncertainty when generating confidence limits for the extreme value distribution parameters. Fortunately a Bayesian analysis

integrating the measurement errors and uncertainties can provide a full posterior distribution of the EVD parameters (Reis and Stedinger, 2005).

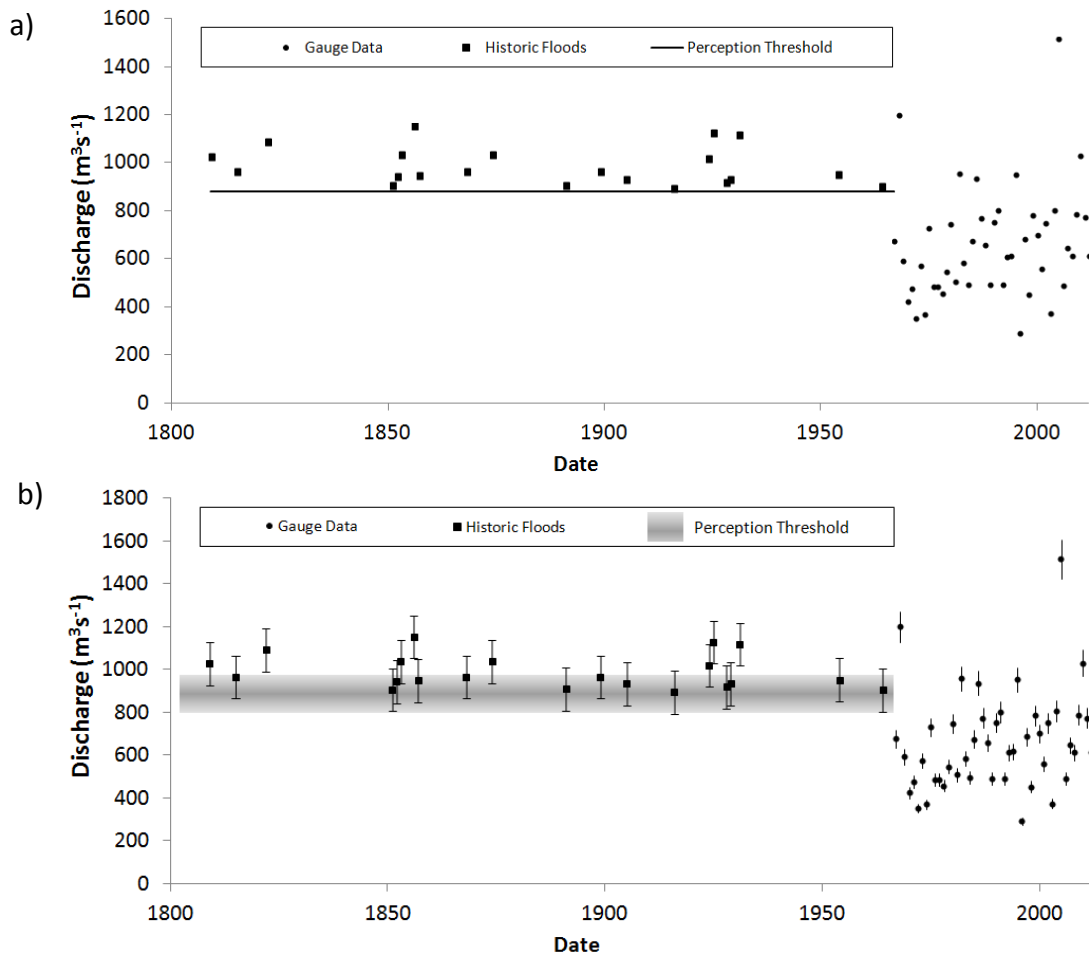


Figure 7.5 Censored time series of peak discharge flood data for the River Eden at the location of the Sheepmount river gauge, Carlisle, Cumbria, UK. 46 years of gauged data are shown with 21 historical flood estimates from 1800. 7.5 b) shows uncertainty in discharge estimates and perception threshold.

### 7.3.1 Land use and channel change

When making use of historic flood data in estimating contemporary flood frequency curves it may be necessary to consider physical changes to the catchment, river channel or floodplain over the historical period that may have affected the likelihood and extent of flooding or the rating curve of the river at the study site.

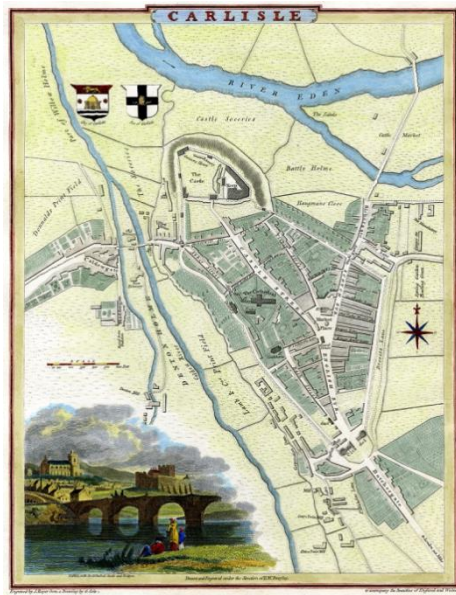
The relationship between land-use change in the catchment and fluvial flood risk is not yet fully understood and is thought to vary with the scale of the catchment under consideration (Pattison and Lane, 2012). Certainly, at the larger catchment scale as is the case for the River Eden at Carlisle there is no evidence that local scale effects of land-use change aggregate downstream (O'Connell et al., 2007).

However, natural or man-made changes to the river channel in or near the study area are likely to have a significant impact on local flood levels (Neppel et al., 2010; Shaw et al., 2010 p. 128). For example the construction of levees designed to limit the extent of flood water will have the effect of reducing the available flood plain storage resulting in a higher water level at the channel for a given discharge. Similarly bridges may have the effect of narrowing the channel and restricting the flow. Changes to the river bed, either in the form of natural changes such erosion or deposition or anthropomorphic activities from dredging are also likely to affect the stage-discharge relationship over time (Jalbert et al., 2011).

A thorough quantification of the effect of this non-stationarity in Carlisle is beyond the scope of this research. However, a brief review of the literature including historic maps (e.g. figure 7.6) of the area provides some indicative guidance.

Figure 7.6 (a) shows that prior to the start of the historical period of this study, part of the River Eden at Carlisle comprised two branches separated by an area called 'The Sands'. By 1821 (figure 7.6 (b)) the Eden no longer has two branches and 'The Sands' is not an island: the southern branch of the Eden had been filled in (Cooke, 1829). The earlier bridges are gone, replaced by the 'Eden Bridge', completed in 1815 and still standing (Eden Bridge, 1932). It is clear that the geomorphology of the Eden changed considerably between 1805 and 1821 and construction of the Eden Bridge may also have altered the river's hydraulics in that period.

a) 1805



b) 1821



c) 1880s



d) 1901

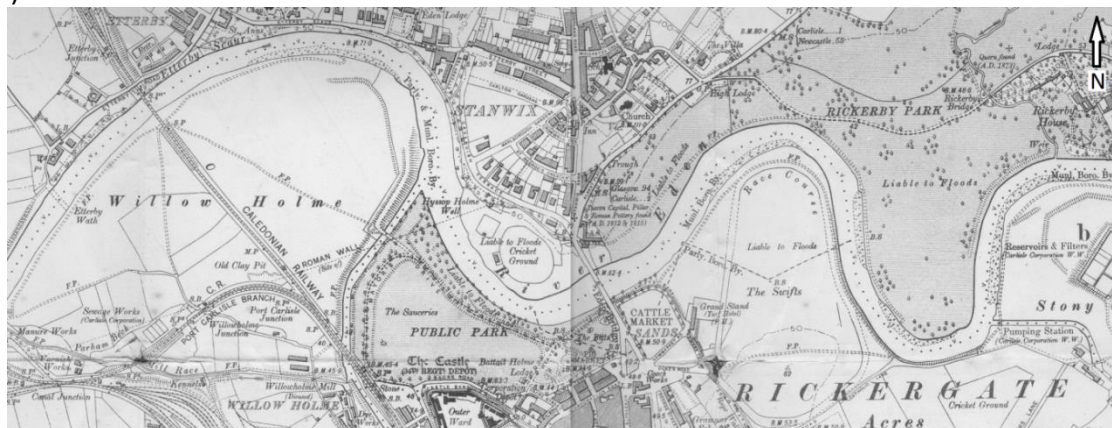


Figure 7.6. Historic maps of the River Eden at Carlisle. (a,b,c) from Cumbria Image Bank (Cumbria County Council, 2014). (d) from Carlisle Library © Ordnance Survey (Ordnance Survey, 2011)

From the evidence above it can be deduced that the filling in of the southern branch of the Eden, the removal of the earlier bridges and the construction of the present bridge all took place between 1805 and 1815. The impact of these changes on the flood levels and discharge is likely to be substantial and largely unquantifiable. So the estimated discharge of  $1025 \text{ m}^3\text{s}^{-1}$  for the 1809 flood is less certain than the discharge estimates for the subsequent floods. For this reason, the discharge estimate for the larger 1809 flood is not used directly, instead, the discharge estimate is given broad upper and lower bounds (see section 7.5.2).

Although the bridge built in 1815 still stands, there was originally a second new bridge completed contemporaneously to the south of the five arches in existence today. Both bridges can be seen in figure 7.7.



Figure 7.7. 1832 engraving of the Eden Bridge completed in 1815, showing the main five arch span over the Eden and the second bridge over the dry branch of the Eden. From Cumbria Image Bank (Cumbria County Council, 2014).

The second bridge spanned the earlier, southern branch of the River Eden that was now dry, but still available for channelling floodwater. The arches forming the second

bridge were demolished in 1969 to make way for a new road scheme (Cumberland News, 2010). The removal of the arches will have further restricted the flow of floodwater past the Eden Bridge in times of flood.

Similarly flood defences on the floodplain in Carlisle have been built and improved in several stages during the historical period. Smith and Tobin (1979) document the construction of embankments in the early nineteenth and twentieth centuries with further improvements in 1932. Most significantly, major improvements to the flood defences were implemented following the 1968 flood which affected more than 400 properties (Atkins, 2011; CEH, 2014). The hypothesis that the removal of the additional bridge arches and the flood defence work carried out over the past century was designed to keep the flows in the river is backed up by expert consultation with a Local Flood Risk Management Advisor for the Environment Agency (interview, Environment Agency FRMA):

“I suppose over the years we have done a lot of work which will keep the flows in the rivers so flow that was a meter below in 1856 might have had the same flow as we’ve had now, but we don’t know”

In terms of within-bank channel changes over the historical period, little or no systematic information is available; however it is likely that the practise of dredging for the purposes of river navigation and, to a lesser extent, flood management would have been more common during the historical period than in recent decades, as is suggested by references to the practice in Carlisle in 1948 and 1963 (Carlisle History, 2014). This has been the trend over the country as cost and environmental concerns have reduced dredging activities (Environment Agency, 2010b).

Overall it seems that the discharge figures for historical floods calculated using the current rating curve formula for the Sheepmount river gauge are likely to be low when compared to the systematic AMAX time series. This would manifest itself as a systematic error/bias in the historic data. In order to put a numeric estimate on this bias, some simulations of the January 2005 flood (see chapter 5) were run using a DEM that had been altered to have the post-1968 defences removed and the additional Eden Bridge arches included. The maximum water level at the Eden Bridge (in the



approximate location of the historic flood marks) was 0.297 m lower when compared against comparable simulations run using the 2005 DEM. By increasing the estimated flood levels for the historic floods in table 7.3 and recalculating the discharges using the rating equation (equation 7.2), the discharge estimates increase by 93 to 101 m<sup>3</sup>s<sup>-1</sup>. Even with this adjustment, none of the adjusted historical floods exceed the peak discharge of the January 2005 flood in agreement with local expert acceptance that the 2005 flood exceeded all floods in the historic period (interview, Environment Agency FRMA).

#### 7.4 Bayes' theorem

The Reverend Thomas Bayes' (1702-1761) famous theorem relating conditional probabilities was published posthumously by Richard Price, a mathematician friend of Bayes in an essay that appeared in the Philosophical Transactions of the Royal Society (Bayes and Price, 1763; Bertsch-McGrayne, 2011). Bayes' rule can be considered very simplistically as a statement that "by updating our initial belief with objective new information, we get a new and improved belief" (Bertsch-McGrayne, 2011). In mathematical form it is written:

$$p(\theta|D) = \frac{\ell(D|\theta)p(\theta)}{\int \ell(D|\theta)p(\theta)d\theta} \quad (7.3)$$

For any probability distribution with parameters  $\theta$ , such that  $p(\theta)$  is the prior distribution (or initial belief) and  $p(\theta|D)$  is the posterior distribution (new and improved belief) after having observed the data,  $D$  (new information).  $\ell(D|\theta)$  is the probability distribution or likelihood of the data ( $D$ ) conditional on the parameters ( $\theta$ ). The integral denominator in equation 7.3 is a normalisation constant ensuring the area under  $p(\theta|D)$  is unity. Consequently Bayes' theorem can be expressed more simply as:

$$p(\theta|D) \propto \ell(D|\theta)p(\theta) \quad (7.4)$$

Notwithstanding the simplicity of equations 7.3 and 7.4, the integral denominator in equation 7.3 often has no analytical solution (Viglione et al., 2013). Furthermore as more than one source of uncertain observed data is used to infer multi-parameter distributions, the expression of the joint posterior distribution tends to become intractable (Lunn et al., 2013). But the ability to cheaply run Markov Chain Monte Carlo



(MCMC) simulations that produce a sample of the desired posterior distribution after a large number of steps brings Bayesian solutions within the reach of a researchers without extensive specialist statistical expertise (Reis and Stedinger, 2005; Robert and Casella, 2004). For the Bayesian analysis in this research, the OpenBUGS software was used (Lunn et al., 2009). BUGS stands for Bayesian inference Using Gibbs Sampling, so the software uses an implementation of the Gibbs sampler (Geman and Geman, 1984) which is a special case of the Metropolis-Hastings algorithm (Hastings, 1970; Metropolis et al., 1953).

#### 7.4.1 The use of Bayesian methods for estimating flood frequencies

In recent years the use of Bayesian techniques for statistical analysis has been gaining currency in many disciplines (Albert, 2009). This change has been facilitated by the availability of cheaper computing power which enables the execution of Monte Carlo methods often needed to complete Bayesian analysis (Lynch, 2007). The steps required to solve a statistical problem are far from straightforward which is perhaps why its use in the field of flood frequency analysis is not common outside academia (Kjeldsen et al., 2014b). However, the ability to design Bayesian methods that combine the use of several data sources and manage uncertainty within those data sources has made it attractive to researchers (see for example Chandler, 2013; Fernandes et al., 2010; Fill and Stedinger, 1998; Gaume et al., 2010; Haddad and Rahman, 2012; Haddad et al., 2012; Kuczera, 1999; Neppel et al., 2010; O'Connell et al., 2002; Parent and Bernier, 2003; Payrastre et al., 2011; Payrastre et al., 2013; Reis and Stedinger, 2005; Reis et al., 2005; Renard et al., 2006a; Ribatet et al., 2007; Seidou et al., 2006; Viglione et al., 2013; Wood and Rodríguez-Iturbe, 1975).

### 7.5 Bayesian inference incorporating systematic and historic data

#### 7.5.1 Selection of extreme value distribution

There is no obvious reason for selecting any particular extreme value distribution (EVD) to use when modelling a distribution such as a time series of AMAX river gauge readings. Fisher and Tippett (1928) assert that for a sequence of independent, identically distributed (iid) random variables, the asymptotic distribution for the largest value in a block of  $n$  values will be of a GEV type as  $n$  tends to infinity. However, in the

real world, the AMAX time series is not bound to eventually converge on a GEV distribution or any other mathematical function, especially when one considers the many factors that affect flood frequencies over time that violate the 'identically distributed' assumption. Most commonly used distributions have 3 parameters (often describing their location, scale and shape), giving them the flexibility to approximate a wide range of 'real' distributions which are obviously not bound to adhere asymptotically to a mathematical formula. This uncertainty, that the EVD chosen to model the natural process is not the real distribution, is referred to as the model uncertainty (Wood and Rodríguez-Iturbe, 1975).

One approach to the issue of model uncertainty is to create a composite distribution of several different EVDs, each allocated a weighting based on how well the distributions fit the available data in an attempt to match the characteristics of the data series (Apel et al., 2008; Apel et al., 2004; Wood and Rodríguez-Iturbe, 1975). However the goodness of fit tests employed to establish the weightings of the candidate EVDs will always be limited because they can only operate within the range of the observed data (Keef, 2014 p. 199). Furthermore, as figure 7.1 suggests, the sampling uncertainty often masks the model uncertainty (Cunnane, 1987) such that it is infeasible to directly estimate the effect of the model error (Kjeldsen et al., 2014a). For these reasons, no attempt is made to represent model uncertainty using a composite of different distribution types; the distribution chosen is selected from the 'goodness of fit' test proposed by Hosking and Wallis (1997) using the gauged data.

The results for the Sheepmount river gauge of the 'goodness of fit test' implemented in the WINFAP-FEH software and described in detail by Kjeldsen et al. (2008) can be seen in table 7.4. The test was run both for a single site analysis and a pooled analysis (see table 7.2 for the pool details). Under the criteria of the goodness of fit test, only the GEV and Pearson Type III distributions should be considered to have an acceptable fit for both single site and pooled analysis because they give an absolute value of  $Z$  less than 1.64. Overall the GEV distribution gives the lowest absolute  $Z$  so it is selected for use in the Bayesian analysis flood frequency at the Sheepmount river gauge. Within extreme value theory, the GEV distribution is considered a sensible choice of distribution for modelling sequences of independent random variables

(Chandler et al., 2014; Embrechts et al., 1997; Jenkinson, 1955) and is commonly used for flood frequency analysis (see for example Gaume et al., 2010; Haberlandt and Radtke, 2014; Kuczera, 1996; Naulet et al., 2005; Neppel et al., 2010).

Table 7.4. Goodness of fit test results for 4 candidate (3 parameter) distributions for the AMAX data from the Sheepmount river gauge in Carlisle, Cumbria. The test is designed such that a distribution is considered to have an adequate fit if the absolute value of  $Z$  ( $|Z|$ ) is less than 1.64 (Hosking and Wallis, 1997; Kjeldsen et al., 2008).

Fitted distribution	Z value for single site analysis	Z value for pooled analysis
Generalised Logistic	-0.0524	2.6418
Generalised Extreme Value	-0.5776	0.0044
Pearson Type III	-0.6805	-0.1981
Generalised Pareto	-1.7613	-5.6678

### 7.5.2 Bayes model

If just the gauged AMAX data were available the likelihood function for gauged data,  $\ell_g(D|\theta)$ , in equation 7.3 is:

$$\ell_g(D|\theta) = \prod_{i=1}^s f_X(x_i) \quad (7.5)$$

In this case  $D$  is the AMAX time series ( $x_1, x_2, x_3, \dots, x_s$ ) of gauged data of length  $s$  years and  $f_X()$  is the probability density function (pdf) for  $X$ . Here the GEV distribution is used which has parameters,  $\theta = \{\mu - \text{location}; \sigma - \text{scale}; \eta - \text{shape}\}^4$  and pdf given by:

$$f(x; \mu, \sigma, \eta) = \frac{1}{\sigma} \left[ 1 + \eta \left( \frac{x - \mu}{\sigma} \right) \right]^{(-1/\eta) - 1} \exp \left\{ - \left[ 1 + \eta \left( \frac{x - \mu}{\sigma} \right) \right]^{-1/\eta} \right\} \quad (7.6)$$

For non-zero  $\eta$  and, when  $\eta = \text{zero}$ :

<sup>4</sup> The notation for the *location*, *scale* and *shape* parameters of the GEV distribution is not consistent across disciplines. For example Kuczera (1996) uses  $m$ ,  $a$  and  $k$  respectively; Viglione et al. (2013) use  $\theta_1$ ,  $\theta_2$  and  $\theta_3$ , and reverse the sign of the shape parameter ( $\theta_3$ ): a common practice in hydrology (Wilks, 2006 p.105).

$$f(x; \mu, \sigma, \eta) = \frac{1}{\sigma} \exp \left[ -\left( \frac{x-\mu}{\sigma} \right) \right] \exp \left\{ -\exp \left[ -\left( \frac{x-\mu}{\sigma} \right) \right] \right\} \quad (7.7)$$

When incorporating data from the historic period, it is necessary to take account of the partial nature of the data. The concept of the ‘perception threshold’ introduced in section 7.3 can be defined as ‘the level above which all flood events were recorded in the historic period’, which can be expressed in terms of probabilities as:

$$Pr(\text{recorded}/X) = 1 \text{ for } X > X_p \quad (7.8)$$

$$Pr(\text{recorded}/X) = 0 \text{ for } X < X_p$$

Where  $X_p$  is the perception threshold and  $Pr(\text{recorded}/X)$  is the probability of there being a recording of a historical flood in any year given the existence of the ‘true’ annual maximum flood,  $X$ . The assumption that there were no large flood events missed during the historic period is justifiable in the case of Carlisle due to the relatively extensive local sources listed in table 7.3. However, the uncertainty in the estimates of the historic floods means that setting a value for the perception threshold isn’t simply a case of choosing a value just below the estimate of the smallest historical flood event. Viglione et al. (2013) employ a conservative approach by setting the perception threshold to the upper bound of the smallest known historical flood. Here, the perception threshold itself is given an uncertain value in the model.

During the historic period of length  $h$  years it is known there were  $k$  floods above the perception threshold,  $X_p$ . For  $k'$  of the historical floods there are estimates of the peak discharge available denoted  $\{y_1, y_2, \dots, y_{k'}\}$ . For the other  $k''$  historical floods it can only be said the flood was somewhere between an upper and lower bound (note:  $k = k' + k''$ ), the upper bounds for these historic floods are denoted  $\{y_{U1}, y_{U2}, \dots, y_{Uk''}\}$  and the lower bounds  $\{y_{L1}, y_{L2}, \dots, y_{Lk''}\}$ . In this case there are 21 known historical floods in Carlisle since 1800, for 20 of those there is an estimate of peak discharge available so  $k' = 20$  and  $k'' = 1$ . For the remaining  $(h-k)$  years of the historical period it can only be said that the maximum flood was below  $X_p$ . On the assumption that annual floods are independent events, following Stedinger and Cohn (1986) and Reis and Stedinger’s (2005) methods for representing censored data and Viglione et al.’s (2013)

method for representing historical floods with upper and lower bounds, the likelihood function for the historical data,  $\ell_h(D|\theta)$  is:

$$\ell_h(D|\theta) = \binom{h}{k} F_X(X_P)^{(h-k)} \prod_{j=1}^{k'} f_x(y_j) \left\{ \prod_{m=1}^{k''} [F_X(y_{Um}) - F_X(y_{Lm})] \right\} \quad (7.9)$$

Which contains terms for the  $h-k$  historical floods below the perception threshold, the  $k'$  floods for which an estimate of peak discharge is available and the  $k''$  historical floods which are known to lie between upper and lower bounds.  $\binom{h}{k} = \frac{h!}{k!(h-k)!}$  is the binomial coefficient and  $F_X()$  is the cumulative density function of the GEV distribution given by:

$$F(x; \mu, \sigma, \eta) = \exp \left\{ - \left[ 1 + \eta \left( \frac{x-\mu}{\sigma} \right) \right]^{-1/\eta} \right\} \quad (7.10)$$

Combining equations 7.5 and 7.9 gives the overall likelihood function  $\ell(D|\theta)$ :

$$\ell(D|\theta) = \binom{h}{k} F_X(X_P)^{(h-k)} \prod_{j=1}^{k'} f_X(y_j) \left\{ \prod_{m=1}^{k''} [F_X(y_{Um}) - F_X(y_{Lm})] \right\} \prod_{i=1}^S f_X(x_i) \quad (7.11)$$

### 7.5.3 Uncertainty in discharge estimates

The Bayes model needed to produce the probability distribution functions for the location, scale and shape parameters of the GEV distribution needs to take account not only of the sampling uncertainty due to the limited data available but also any random and possibly systematic (bias) data errors in the gauged and historical flood estimates. Fortunately the MCMC can incorporate data uncertainty relatively easily with little impact on execution time (Reis and Stedinger, 2005). Various approaches to representing the error in gauged and historical readings have been employed (see for example Neppel et al., 2010), such as a log-normally distributed error for gauged data (Kuczera, 1996) and a uniformly distributed error with upper and lower limits for historical flood estimates (Viglione et al., 2013). The approach for random errors taken here is to assume both gauged and historical discharge estimates are affected by a normally distributed error about the estimated figure with the standard deviation representing the confidence in the accuracy of the figure. As the literature reviewed on accuracy of gauged data suggests (section 7.2.3), the error in the gauge readings is

likely to increase with the magnitude of the readings, so the model uses a standard deviation which is a percentage of the gauge reading. This is not necessarily the case for historical estimates of floods. Consequently the model uses the same standard deviation for the uncertainty in all historical discharge estimates rather than a percentage of the estimate (see figure 7.5 b). Additionally the likelihood of a systematic bias in the historical discharge should be considered and is discussed in section 7.5.5.

#### 7.5.4 Bayes model parameters and prior distributions

The model parameters used in the Bayes model are described in table 7.5. The first three entries in the table are the prior distributions for the GEV model parameters ( $\theta = \{\mu, \sigma, \eta\}$ ). The approach recommended by Kuczera (1999) is to use informative priors based on a regional flood frequency analysis. Another approach is to assume prior independence of the GEV parameters using broad, uniform distributions for the location ( $\mu$ ) and scale parameters ( $\sigma$ ), then giving some sort of geophysically representative prior for the shape ( $\eta$ ) parameter: a beta distribution in the case of Martins and Stedinger (2000); or a Gaussian distribution in the case of Neppel et al. (2010). For the UK there is no obvious indication of what would make up a statistically or geophysically representative prior distribution, so uniform (non-informative) priors were used for all three GEV parameters.

The default value for the gauged data uncertainty is based on the literature review (section 7.2.3) where an error of  $\pm 10\%$  is roughly equivalent to a standard deviation of 5%. The default value for the historical adjustment factor is based on the historical flood modelling described in section 7.3.1. The uncertainty in the historical floods and the perception threshold are more subjective and were confidence limits thought to be wide enough to cover most uncertainties in the historical flood estimates.

Table 7.5. Bayes model parameters and prior distributions.

Parameter	Description	Default value(s)	Range used in sensitivity analysis
<b>Prior distribution for GEV distribution parameters</b>	$\mu$ Location	0 to 1600	
	$\sigma$ Scale	0 to 500	
	$\eta$ Shape	-0.5 to 0.5	
<b>Gauged uncertainty</b>	Uncertainty (standard deviation of normally distributed perturbation) applied to gauged AMAX readings. Percentage of readings.	5%	0% to 20%
<b>Historical uncertainty</b>	Uncertainty (standard deviation of normally distributed perturbation) applied to historical flood estimates. Absolute value.	$50 \text{ m}^3\text{s}^{-1}$	$0 \text{ m}^3\text{s}^{-1}$ to $316 \text{ m}^3\text{s}^{-1}$
<b>Historical adjustment factor</b>	Factor applied to estimates of historical flood discharge to take account of construction of flood defences and reduction in dredging activities.	$97 \text{ m}^3\text{s}^{-1}$	$-200 \text{ m}^3\text{s}^{-1}$ to $300 \text{ m}^3\text{s}^{-1}$
<b>Perception threshold</b>	Minimum value of floods in the historic period included in the historic flood record.	$900 \text{ m}^3\text{s}^{-1}$	$740 \text{ m}^3\text{s}^{-1}$ to $1100 \text{ m}^3\text{s}^{-1}$
<b>Perception threshold uncertainty</b>	Uncertainty (standard deviation of normally distributed perturbation) applied to perception threshold. Absolute value.	$50 \text{ m}^3\text{s}^{-1}$	$0 \text{ m}^3\text{s}^{-1}$ to $140 \text{ m}^3\text{s}^{-1}$
<b>Chain length</b>	Number of MCMC steps per model run	20,000	20,000 to 100,000
<b>Burn-in steps</b>	Number of MCMC steps disregarded as burn-in	5,000	5,000 to 20,000

### 7.5.5 Sensitivity Analysis

In order to establish how the model behaviour response changed as the parameters were altered, a sensitivity analysis was performed. The direct model output consists of the posterior estimates for the mean and standard deviation of the three GEV parameters, but the mean and 95% confidence limits for the 0.01 AEP flood from the flood frequency curve derived from the model output give a more useful metric for assessing the sensitivity. Figure 7.8 shows the sensitivity of the model while varying six model parameters.

Figure 7.8 (a and b) show that the model is insensitive to the uncertainty both in the gauge readings and the historical flood estimates until they reach levels towards the upper end of the scale. All the graphs in figure 7.8 use the 0.01 AEP (100 year return period) flood as the key metric, which is towards the higher end of the flood frequency curve. This metric will be more influenced by only the bigger floods in the time series. Extending the uncertainty of the gauged and historical time series beyond that which is physically realistic will enhance the influence of the medium sized floods on the upper end of the flood frequency curve. Figure 7.8(d) shows the model is sensitive to the value chosen for the perception threshold across all values; however there is no reason to select a value far from that derived from the historical flood data. Overall the model shows the greatest sensitivity to the historical adjustment factor (figure 7.8(c)) which shows the importance of selecting a realistic value for this parameter. It should be noted that since this factor is added directly to the historical flood estimates, this parameter combines with the historical uncertainty parameter to cover stochastic (random) and systematic (bias) error.

### 7.5.6 Results

Running the model with the default parameters gives the posterior distributions for the GEV model parameters shown in table 7.6. Figure 7.9 shows the resulting flood frequency curve with confidence limits plotted using output from the Bayes model. Figure 7.10 transposes the flood frequency curves for the single site analysis using the WINFAP-FEH software (GEV distribution fitted using L-Moments) with the flood frequency curve generated using the Bayes model. The benefit of the use of the Bayes model can be seen in the narrower confidence limits, which are also evident in the



figures for the confidence limits of the design floods shown in table 7.6. The model gives an AEP for the January, 2005 flood of 0.000194 (return period 262 years) with 95% confidence limits of 0.014 to 0.000246 (return periods: 70 years to 4060 years).

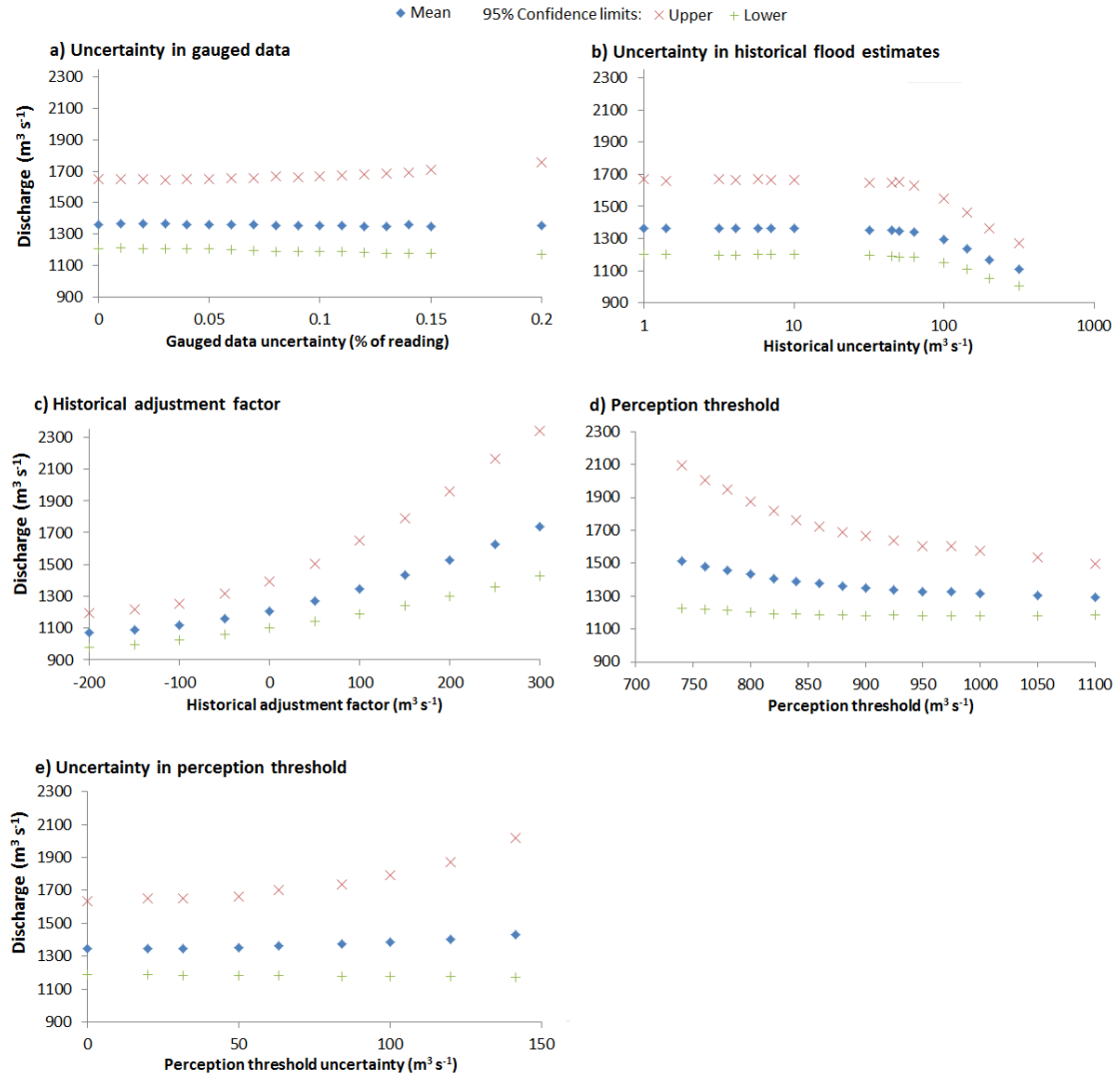


Figure 7.8. Sensitivity of the Bayes model to model parameter variation. The figures shown are for the mean value for the 0.01 AEP (100 year return period) flood with 95% confidence limits.

Table 7.6. Posterior distribution for the GEV parameters from the Bayes model.

Parameter	Mean	Standard Deviation
$\mu$ – location	562.0	22.92
$\sigma$ – scale	160.1	13.05
$\eta$ – shape	0.02423	0.07265

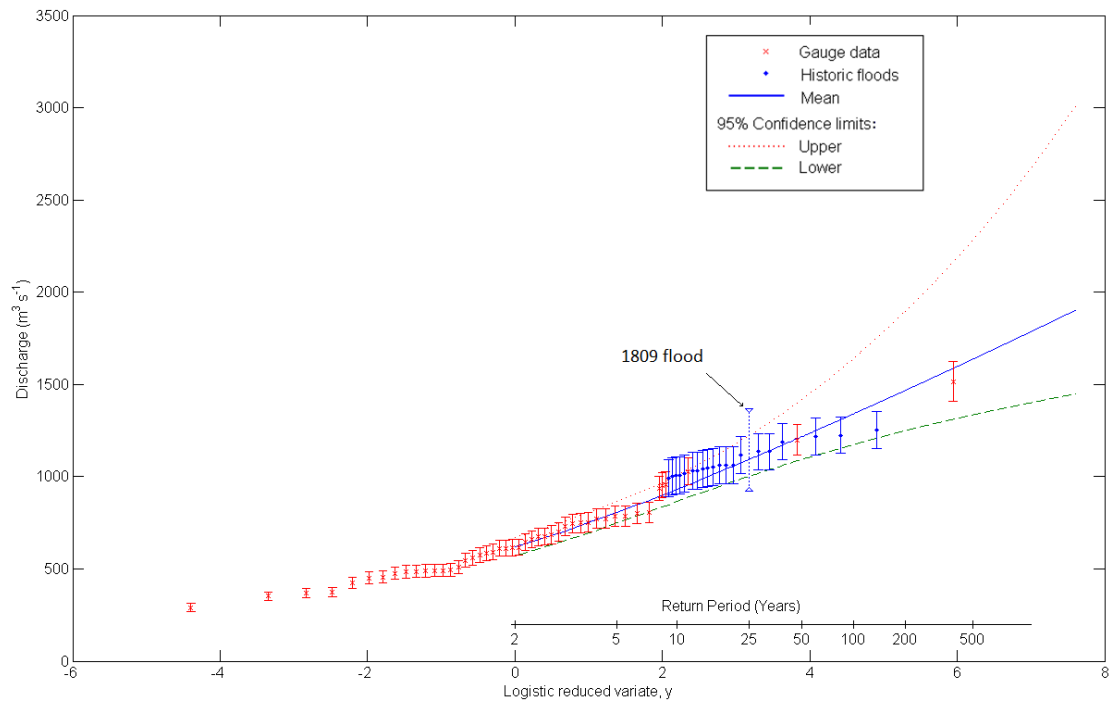


Figure 7.9. Flood frequency curve of the River Eden at Sheepmount showing 95% confidence limits, derived using the Bayes model described in section 7.5.2. Also shown are the gauge readings from the Sheepmount river gauge plotted using Gringorten plotting position formula and the historical flood estimates plotted using the method described by Bayliss and Read (2001). The upper and lower limits for the 1809 flood are highlighted.

## 7.6 Discussion and Conclusion

This chapter has demonstrated how a Bayes model can be constructed to make use of uncertain historical data combined with systematic data from a gauging station to produce a flood frequency curve with confidence limits. The data in table 7.7 show how the addition of the historical data is advantageous because it can lead to a significant reduction the confidence intervals of the flood frequency curve across all return periods, and this is the case even when historical flood estimates are treated as highly uncertain. Indeed, the ‘bootstrap’ method used to estimate the confidence intervals for the single site analysis is often found to give lower uncertainty estimates than other, comparable methods using the same data (Hall et al., 2004; Kjeldsen et al., 2014a).

In addition the model employed here can incorporate the inclusion of a subjective adjustment factor resulting from consultation with stakeholders with local hydrological knowledge. The ability to add possibly subjective, expert hydrological information to the Bayesian model (also see Viglione et al., 2013) can perhaps assuage the concern that flood frequency analysis is dominated by statistical analysis rather than hydrology (Singh and Strupczewski, 2002). However, within the Bayesian framework it is important to communicate transparently how subjective factors such as this are incorporated in the model and how the model responds.

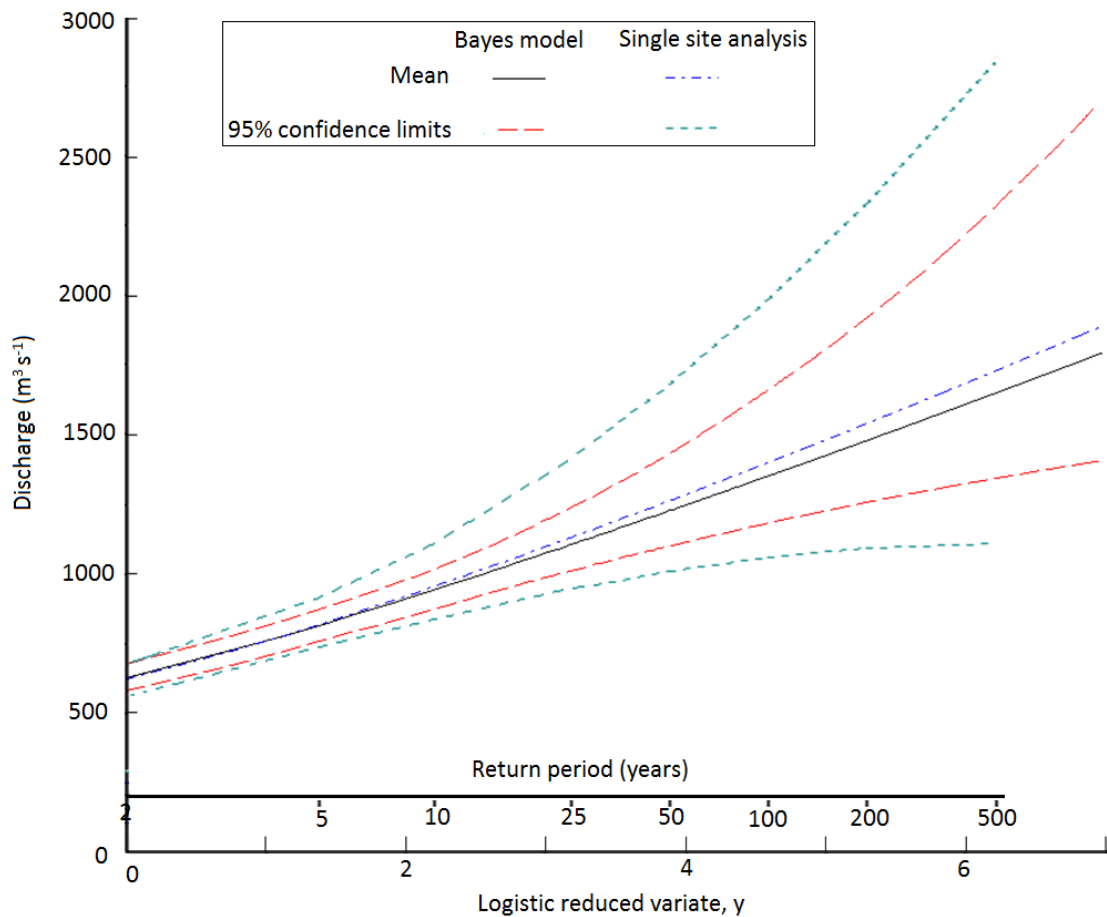


Figure 7.10. River Eden at Sheepmount flood frequency curves with 95% confidence limits showing comparison of curves derived using the Bayes model with the single site analysis using WINFAP-FEH software (GEV distribution fitted using L-Moments).

Table 7.7. Estimates of the discharge at the Sheepmount gauging station for certain design floods with 95% confidence intervals, comparison of single site analysis (GEV distribution fitted using L-Moments) with results of Bayesian model. Also shown is the percentage reduction in the 95% confidence interval of the design floods achieved by implementing the Bayesian model. The results of running the Bayesian model using only the systematic data (no historic flood estimates) is included for comparative purposes.

<b>AEP</b> <b>(return period, years)</b>	<b>0.5</b> <b>(2)</b>	<b>0.0133</b> <b>(75)</b>	<b>0.01</b> <b>(100)</b>	<b>0.001</b> <b>(1,000)</b>
<b>Mean Discharge (<math>\text{m}^3\text{s}^{-1}</math>)</b> <b>(95% confidence interval)</b>				
<b>Single site analysis,</b> <b>GEV, L-Moments</b>	617 (558-678)	1342 (1036-1853)	1400 (1056-1983)	1876 (1123-3295)
<b>Bayesian model</b> <b>output</b>	621 (574-670)	1289 (1144-1538)	1341 (1177-1631)	1766 (1405-2588)
<b>Reduction in</b> <b>confidence interval</b>	20%	52%	51%	46%
<b>Bayesian model,</b> <b>using systematic data</b> <b>only</b>	623 (562-690)	1408 (1142-2037)	1471 (1178-2200)	2000 (1421-4020)

Even though the benefits of implementing a Bayes model can clearly be demonstrated, it is still the exception rather than the rule when estimating flood frequency curves and is not in evidence outside academia. This is unsurprising given the lack of commercial software that would assist in the development and testing of Bayesian models. At the moment the model employed for this project has only been used for the data from Carlisle. But there is no reason why the model would not work at other sites where there is a mixture of gauged and historic data either in the form of uncertain estimates of historic floods (censored historic time series), or just knowledge of large floods in the past with no estimate of the peak discharge (binomial censored time series) (Reis and Stedinger, 2005). If the model proved adaptable to other sites could it be packaged up with a 'user friendly' interface that would allow more

widespread use among the flood risk management community? The changes required to adapt academic software for commercial distribution and use are considerable. As well as improving the user interface, error handling and support infrastructure, one particular hindrance is that, when using Bayesian MCMC analysis, it is frequently not obvious when the simulation is not converging on the posterior distribution (Lunn et al., 2013 p. 72). For all the model runs in this project 20,000 iterations with 5,000 taken as burn-in was sufficient to achieve stationarity for the GEV parameter distributions. But this may not be the case for other locations with different sets of data. There are techniques for formally identifying convergence, for example Plummer et al. (2006), but none are completely reliable (Lunn et al., 2013 p. 75). So it is currently difficult to envisage a software package for estimating flood frequencies in this way that could be used by practitioners with little knowledge of the underlying techniques.

The flood frequency curve in figure 7.9 is used in the next chapter to simulate one thousand year time series of flood hydrographs for the River Eden at Carlisle.

## Part 3. UNCERTAINTIES IN DESIGN FLOODS AND THEIR IMPLICATIONS FOR MANAGEMENT

## Chapter 8. Simulating design floods in Carlisle

### 8.1 Introduction

In the UK and elsewhere the severity of a flood event is often defined by the ‘return period’ of the flood. The convenient term used to enumerate a return period: “the hundred year flood” is shorthand for *the flood that would on average only be exceeded at this location once every one hundred years* (IH, 1999). Even though the Environment Agency is keen to replace the return period terminology with the less ambiguous ‘annual exceedance probability’ (AEP) (Deputy Director FCRM Environment Agency, 2014), the key return periods for the design floods are still the same and, importantly, are often categorised by the maximum discharge recorded or estimated during the flood event (Shaw et al., 2010).

One of the aims of this project is to assess the impact of design floods of 0.01 AEP in the city of Carlisle along with a quantification of the uncertainty of the floods. In chapter 5 a hydraulic flood model was described that was calibrated against the observational data of the January 2005 flood in Carlisle and used the recorded hydrographs of the flood as boundary conditions. In chapter 7, the flood frequency curve for Carlisle was derived from the AMAX time series from the Sheepmount river gauge and records of historical floods in Carlisle. This suggests the 0.01 AEP (one hundred year return period) flood could be simulated simply by running the calibrated flood model with a hydrograph scaled such that the peak discharge matches the 0.01 AEP discharge. The uncertainty in the 0.01 AEP flood could be represented by running a Monte Carlo simulation that captured the uncertainty in the hydraulic flood model by sampling from the set of behavioural simulations of the calibrated hydraulic model and the uncertainty in the flood frequency curve by sampling from the PDF’s of the parameters of the flood frequency curve. The same approach could be taken for the 0.001 AEP (one thousand year) flood and any other design floods that are relevant to policy makers. However, if this approach were taken it would ignore two aspects of uncertainty that have been shown to have material consequences when calculating flood risk: firstly the spatial dependence between the flows in different rivers in the study area (Neal et al., 2012); secondly the duration of the flood, not just the peak

discharge, affects the severity of the flood, so the variability of the shape of the flood hydrograph should also be represented (Apel et al., 2009b). For a discussion of some of the many further factors affecting uncertainty such as seasonality, defence failure etc. see section 8.10.

For this chapter the probabilistic flood model described in chapter 5 was combined with the flood frequency curve derived in chapter 6 into a single model for estimating flood risk in Carlisle that also incorporates uncertainty due to the spatial dependence of the rivers and the variation in flood duration. The model was used to produce probabilistic flood risk maps for the design floods for Carlisle which were then analysed using property, population and damage data to give estimates of the consequences of uncertainty in flood risk in terms of the risk to population and properties.

The first two sections of this chapter (sections 8.2 and 8.3) describe the techniques used for accounting for these two sources of uncertainty resulting in a set of 100, thousand year simulations of annual peak flows for Carlisle. The model set-up and preparation of the simulations is described in the next 2 sections (8.4 and 8.5), then section 8.6 examines the sensitivity of the model to the model parameters. The results of driving the hydraulic flood model with each of the thousand year simulations are presented as probabilistic flood risk maps for Carlisle in section 8.7. By using information from the National Population database (Smith and Fairburn, 2008) and National Receptor Dataset (Environment Agency, 2011e) it is possible to calculate key metrics on the properties, infrastructure, and population affected by the uncertainty in the flood risk zones (section 8.8). Finally, the uncertainty in financial risk is estimated using the methods in the Multi-Coloured Manual (Penning-Rowsell et al., 2013) (section 8.9) followed by a discussion (section 8.10) on the extent of all sources of uncertainty and conclusion (section 8.11).

## 8.2 Spatial dependence between rivers

Whilst flooding near the coast where the risk is strongly dependent on both tidal and fluvial systems often receives special consideration (see Hall et al., 2014 for a case study of the Thames Estuary), the issue of spatial dependence between rivers away from tidal influence is frequently overlooked. The problem arises near river



confluences where flooding can be caused by either of the watercourses or, crucially, a combination of the two rivers.

In Carlisle, the main river, the Eden, is joined by two smaller tributaries, the Rivers Caldew and Petteril. All three rivers are known to flood, and this happened simultaneously in January 2005 when extreme flows on all three rivers contributed to inundation of the city (Environment Agency, 2006). This situation is not unexpected due to the proximity of the catchments of the rivers.

As previously discussed, the Environment Agency calculates fluvial flood risk in the UK by estimating the extent of flooding likely to be caused by river flows matching certain return periods estimated from the flood frequency curve at the site (Shaw et al., 2010). Flooding from each river is typically estimated separately which means no account is taken of any correlation between connected watercourses (Bradbrook et al., 2005). Common sense and much research tells us that there is in fact a spatial correlation between flows on different rivers and that the flood risk near the confluence of rivers must be considered as a function of the flow and correlation of the rivers (Keef et al., 2009a; Lamb et al., 2009). For example, consider points C,D,E and F in figure 8.1. Points C and D are on the edge of the high flood risk ( $\geq 0.01$  AEP) zone from Rivers A and B respectively, so it can be said the annual risk of fluvial flooding is 1% for points C and D. Point E is on the edge of the high flood risk zone of both rivers. If there were no correlation between floods on the two rivers, the annual flood risk at point E would be sum of the risk of flooding from each river independently, which is very nearly 2%. But in reality the flood risk at points E and F is not a simple linear combination of the flood risk from each river, but is influenced by the spatial correlation between floods on the rivers. For example, it may be that if a 0.02 AEP (one in fifty year) flood occurs simultaneously on both rivers, water from River A backing up the channel of River B will cause flooding at point F even though it is outside the 0.01 AEP flood zone of each river separately. The correlation between the flows on the rivers is not perfect so the flood risk near the confluence of rivers should be considered a function of both the discharge and spatial correlation between the rivers (Keef et al., 2009a; Lamb et al., 2009).

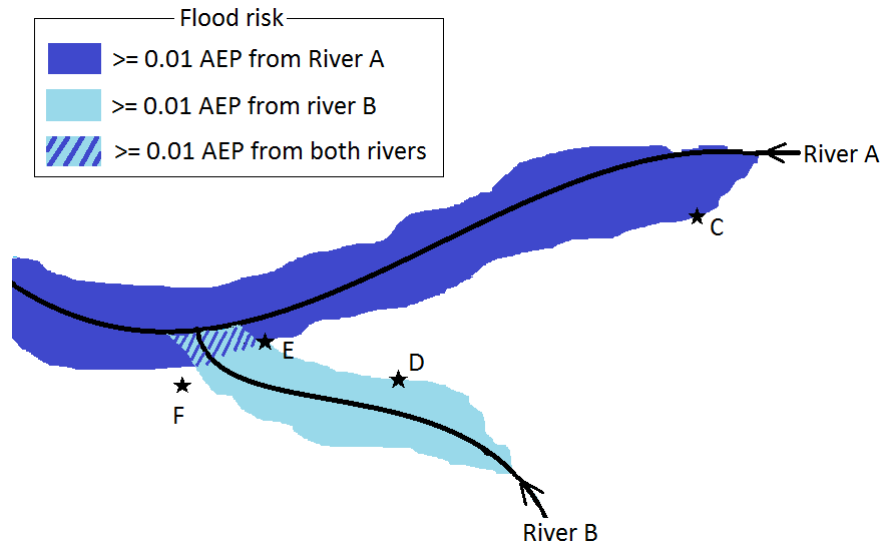


Figure 8.1. Example river system showing the extent of the zones of high flood risk ( $\geq 0.01$  AEP) for two rivers (black lines).

In theory, the use of a “rainfall-runoff method” of estimating flood frequencies within a catchment by driving a spatially distributed hydrological model with simulated rainfall (England et al., 2014; Li et al., 2014) could be extended to cover multiple catchments, and this would provide the necessary spatial correlation information for estimating flood risk near the confluences (see for example Blazkova and Beven, 2004; Corelogic EQECAT, 2014; Wheeler et al., 2005). This would require extensive model set up and introduce additional levels of uncertainty within the statistical rainfall simulations and hydrological models (Keef et al., 2009b). Instead, this research uses a dataset from a previous research project on Carlisle by Neal et al. (2012) that captures the spatial correlation between the extreme flows of the River Eden and its two tributaries that meet at Carlisle: the Rivers Caldew and Petteril (see figure 8.2).

Keef et al. (2009a; 2009b) and Lamb et al. (2010) have applied the work on multivariate extreme value theory by Heffernan and Tawn (2004) using copulas to determine the dependence structure (Joe, 1994; Joe, 2014) to map the spatial dependence of extreme river flows and precipitation across Great Britain. Later, Neal et al. (2012) also used the dependency model of Heffernan and Tawn (2004) to model the joint distribution of the extreme flows of the Rivers Eden, Caldew and Petteril in Carlisle.

Neal et al. (2012) followed the approach of Keef et al. (2013) in simulating multiple sets of flood events expected to occur on average in a 1,000 year period. This was done by fitting a generalised Pareto distribution to peaks over threshold (POT) data from the six gauging stations marked in figure 8.2 and using a copula function to describe the dependence structure (Neal et al., 2012). Next Neal et al. applied a block bootstrap procedure to resample the dataset 100 times to give a set of 100 simulations of 1,000 years of flood events on the three rivers. The purpose of the bootstrap resampling was to provide an estimate of the uncertainty due to the short record lengths of the gauges; ideally, more bootstrapped samples would have been generated, but the number was limited to 100 by the available computing power. But even with 100 resamples Neal et al. (2012) estimate the errors in the uncertainty of the resulting probabilistic flood map due to the resampling size to be only 4%. Additional details of the dependency model, its application to the river flows in Carlisle and the resulting sets of 1,000 years of flood events can be found in Heffernan and Tawn (2004), Lamb et al. (2010), Neal et al. (2012) and Keef et al. (2013).

The estimates for the flow frequencies used to generate the simulated sets of 1,000 year flood events described in the previous paragraph are conditioned on the river gauge data from the six gauges marked in figure 8.2. However, chapter 6 describes the derivation of the flood frequency curve for the River Eden at the location of the Sheepmount gauge using both gauged flows and historic flood estimates. By using the simulated flows for Sheepmount from the flood frequency curve derived in chapter 6 instead of the Sheepmount flows provided by Neal et al. (2012), the spatial dependence between the rivers in the site are retained, but the flows for the Eden adhere to the frequency curve with reduced uncertainty derived in chapter 6. The simulated flows from Neal et al. (2012) for the Rivers Caldew and Petteril are used unaltered.

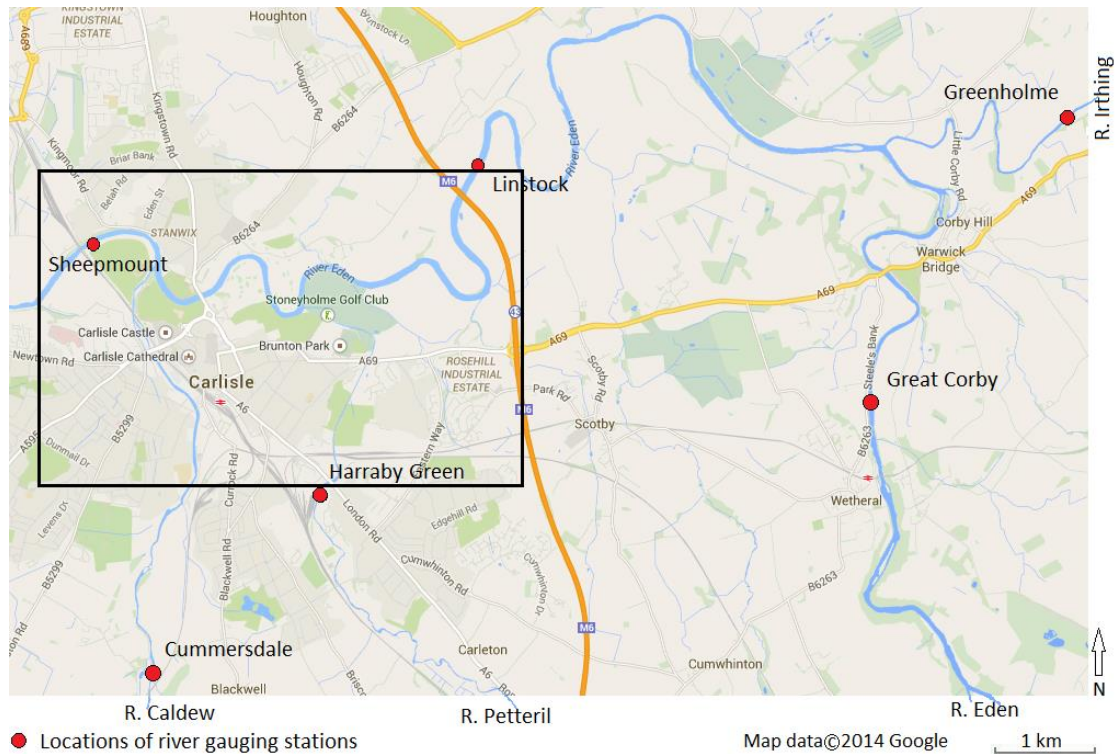


Figure 8.2. Map of Carlisle, UK and surrounding areas showing the river network and locations of the river gauges used to derive the spatial dependence between rivers.

The black box shows the extent of the hydraulic flood model.

### 8.3 Variability of flood hydrograph

The peak flow as estimated by the flood frequency analysis is only one metric influencing the consequences of a flood. The volume of water and the gradient of the rising and falling limbs of the flood will also contribute to the inundation extent and damage caused (Apel et al., 2004; Grimaldi and Serinaldi, 2006; McMillan and Brasington, 2008; Neal et al., 2012; Pattison et al., 2014). These factors are represented in a flood simulation by variations in the shape of the flood hydrographs and the relative timings of the peak discharge of the rivers flowing into the study area. Both Neal et al. (2012) and Pattison et al. (2014) acknowledge the importance of these factors when testing the sensitivity of the hydrograph in Carlisle to the duration, timing and sequencing of the tributary flood peaks.

One way of establishing the nature of the flood hydrograph is to use a hydrological model of the catchment to identify the *synthetic unit hydrograph* for the site of interest. The unit hydrograph as defined by Sherman (1942) is the hydrograph output

of the hydrological model when entire catchment is subjected to constant precipitation for a unit of time. For example the 1 day unit hydrograph might result from a simulated rainfall of  $1\text{mm hr}^{-1}$  for 24 hours. By varying the intensity and duration of the precipitation a range of unit hydrographs can be created (Shaw et al., 2010). The synthetic unit hydrograph method is still a popular modelling technique for ungauged basins, albeit in various different forms and modifications (Singh et al., 2014). Where high frequency river gauge readings are available, the requirement to add a hydrological model and synthetic precipitation data to the modelling chain sometimes means it is more efficacious to characterise the flood hydrographs with associated uncertainty from the exiting discharge data from previous events as is described by Apel et al (2004), Grimaldi and Serinaldi (2006), Renard and Lang (2007) and Domeneghetti et al. (2012a; 2012b). This was the approach favoured for the Carlisle case study in this project.

To characterise the variation in flood durations and flood peak arrival times, it was necessary to examine the 15 minute flow data from the Sheepmount, Cummersdale and Harraby Green gauges (see figure 8.2). Hydrographs for all peaks above a certain minimum flow were extracted from the 15 minute flow data by first identifying the time of the peak then extracting the data points before and after the peak that were above a certain base flow. The values for the minimum peaks and base flow were selected to give a reasonable number of easily identifiable peaks from the available data. For the purposes of this exercise, there was no need to ensure statistical independence of the peaks. Therefore if two peaks arrived close together such that the flow did not drop below the defined base flow between the peaks, then the peaks were separated manually. This was only necessary on three occasions, and each time the effect on the overall volumes of the peaks in question was slight. The data is summarised in table 8.1.

Table 8.1. Summary peak hydrograph information extracted from 15 minute flow data for gauging stations at Sheepmount, Cummersdale and Harraby Green.

Station	Sheepmount	Cummersdale	Harraby Green
<b>River</b>	Eden	Caldew	Petteril
<b>Station ID</b>	76007	76809	76010
<b>Record start date</b>	31/12/1975	7/7/2003	7/7/2003
<b>Record end date</b>	14/6/2014	14/6/2014	14/6/2014
<b>Base flow (<math>\text{m}^3\text{s}^{-1}</math>)</b>	200	40	10
<b>Minimum peak flow (<math>\text{m}^3\text{s}^{-1}</math>)</b>	550	160	33
<b>Number of peaks extracted</b>	46	12	25

Initially the relationship between the total volume of water ( $v$ ) for each and the product of the peak duration ( $d$ ) multiplied by peak height ( $h$ ) was examined. This would give an indication of how closely the peak could be approximated to a triangle. If  $v \approx 2dh$  then the peak shape can be considered triangular. Fitting a linear relationship to the peaks gave  $v \approx 1.92dh$  ( $R^2 = 0.965$ ) for Sheepmount  $v \approx 1.95dh$  ( $R^2 = 0.931$ ) for Cummersdale and  $v \approx 1.72dh$  ( $R^2 = 0.966$ ) for Harraby Green. Certainly the Sheepmount and Cummersdale peak show a strong triangular approximation. The volumes of the Harraby Green peaks are lower than ideal triangles; this may be due to the lower flows of the River Petteril making it harder to identify the approximate start and end points of the peaks. It was decided, considering the contribution of the Petteril to the overall flows, that the peaks for all three rives can be modelled as triangular. This strong correlation between flow and volume is commensurate with the findings of MacMillan and Brassington (2008) who also use triangular design hydrographs for flood risk assessment. Figure 8.3 shows some sample flood

hydrographs recorded at the Sheepmount, Cummersdale and Harraby Green gauges overlain by the corresponding triangular, 'design flood' approximations.

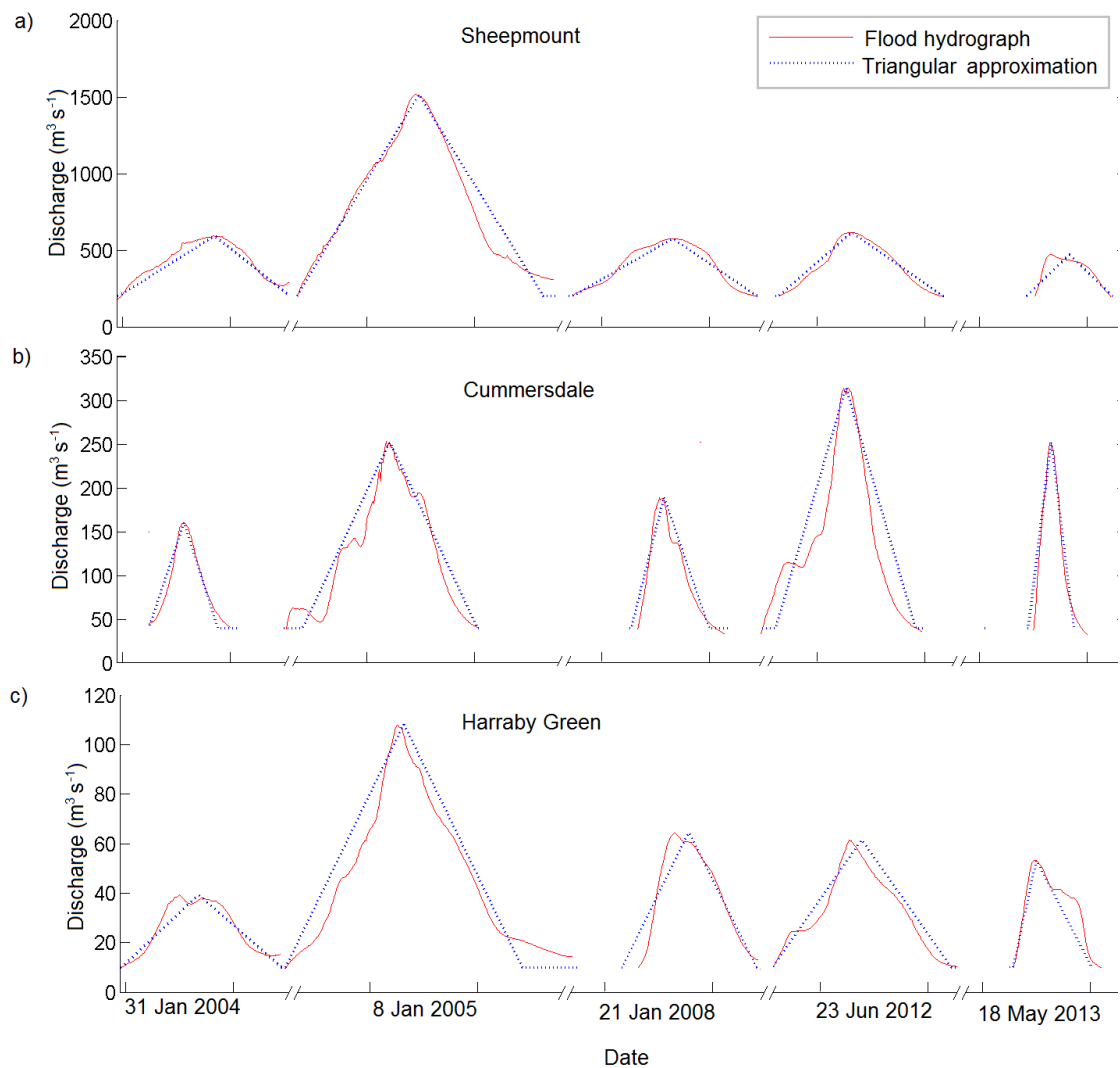


Figure 8.3. Sample flood hydrographs recorded at the a) Sheepmount, b) Cummersdale and c) Harraby Green gauges. Triangular approximations of the hydrographs are shown as dotted lines.

Next the relationship between the peak height and duration was considered. Figure 8.4 shows that all peaks for the Sheepmount gauge lie between two linear trendlines:  $d = 0.11p$  and  $d = 0.037p$ . These trendlines provide approximate minimum and maximum durations (in hours) for a triangular flood hydrograph given the peak discharge. When simulating the triangular flood hydrographs for the River Eden, the duration was a randomly drawn from a uniform distribution between 0.11 and 0.037 multiplied by the peak discharge (in  $\text{m}^3\text{s}^{-1}$ ). By identifying the flood events on the

Caldew and Petteril that coincide with flood events on the Eden, a strong linear correlation between the durations of the flood hydrographs was found. Consequently, the durations of the simulated flood hydrographs for the two tributaries were set as a fixed percentage of the duration of the flood hydrographs on the Eden. Specifically, the durations of the Caldew and Petteril hydrograph widths were set to 66% and 94% of the Eden hydrograph width respectively.

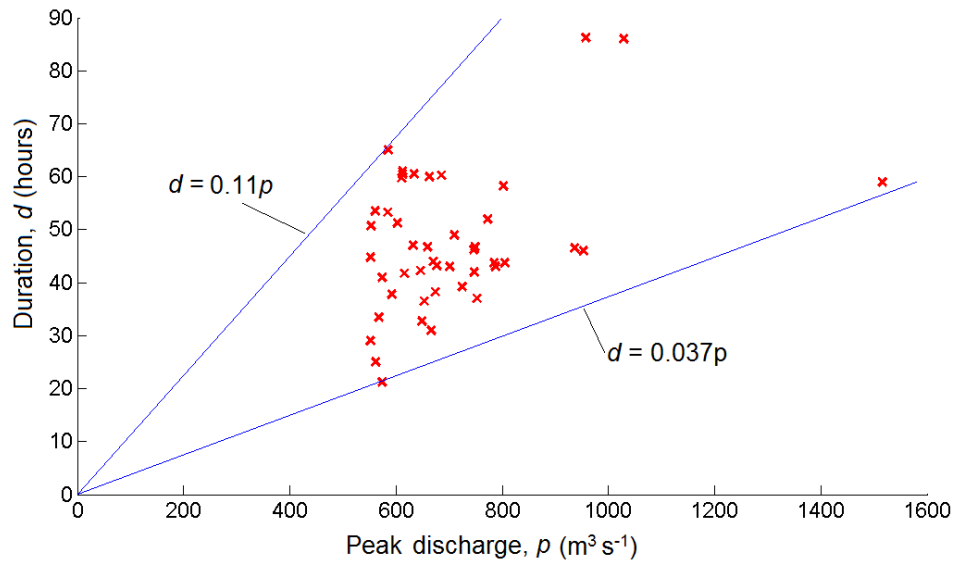


Figure 8.4. Peak discharge for all floods over  $550 \text{ m}^3 \text{ s}^{-1}$  recorded by the Sheepmount gauge between 31/12/1974 and 14/6/2014 plotted against approximate duration (in hours) of the flood peak. The lines  $d = 0.11p$  and  $d = 0.037p$  show the range of flood peak duration for a given peak discharge.

The relative timing of the peak discharge of the rivers was also shown by Neal et al. (2012) to influence the depth and extent of flooding during the January, 2005 event. In order to account for this, the difference in arrival time of peak discharges were examined for the flood events recorded on the River Eden at Sheepmount that coincided with a flood on one of the two tributaries. The resulting 24 data points showed that generally the flood peaks on the Caldew and Petteril preceded the Eden peak by between 0 and 7 hours. This result is expected due to the relative size of the catchments of the Rivers Caldew ( $244 \text{ km}^2$ ) and Petteril ( $160 \text{ km}^2$ ) compared to the River Eden ( $2,286 \text{ km}^2$ ) (CEH, 2011). Consequently, the lead time in hours for these flood peaks on the tributaries was drawn from a uniform distribution between 0 and 7.



## 8.4 Hydraulic model set up

Chapter 5 describes in detail how the 1-D/2-D LISFLOOD-FP flood modelling software (Bates and De Roo, 2000; Bates et al., 2010) was set up and calibrated against the January 2005 flood in Carlisle. The GLUE methodology of Beven and Binley (1992) captured the uncertainties in the model structure, the model parameters and the observational data. The results of the GLUE analysis are a sub-set of the model parameter sets that are considered 'behavioural' with a weighting applied to each behavioural parameter set according to how well the simulation matched the observational data. In chapter 5, a Latin Hypercube Sampling (LHS) method (Saltelli, 2008) was used to vary the 5 model parameters and generate a Monte Carlo simulation of 999 simulations. Of the 5 model parameters, 3 were discharge multipliers to modify the magnitude of the discharge in the hydrographs of the three rivers to take account of uncertainty in the discharge measurements. However, for the purposes of this chapter, the discharge uncertainty is captured by the resampling of the 1,000 year flood events and the uncertainty in the flood frequency curve for the River Eden at Sheepmount derived in chapter 7. Consequently, only the channel roughness ( $n_{ch}$ ) and floodplain roughness ( $n_{fp}$ ) model parameters are varied in the LHS for the hydraulic flood model simulation. The GLUE analysis results in 470 behavioural parameter sets weighted between 0 and 1. For each of the model simulations run for this chapter, one of the sets of behavioural channel and floodplain roughness parameters was randomly selected according to its weighting. The full list of model parameters is summarised in table 8.2.

## 8.5 Preparation of Monte Carlo simulations

Combining spatially correlated sets of flood peak data, hydrograph shape characteristics and the hydraulic model set up can be done using a Monte Carlo framework comprising many flood simulations of the area of interest. As long as sufficient simulations are run, the uncertainty due to the hydraulic flood modelling, frequency analysis and hydrograph shapes and timings can be captured and quantified. Not only can the Monte Carlo simulation results be used to provide probabilistic flood maps for the area, but also some indication of the contribution to the overall uncertainty of the individual sources can be extracted (for example Apel et al., 2008; Di

Baldassarre et al., 2009; Di Baldassarre et al., 2010; Neal et al., 2012; Stephens and Bates, 2012). This section describes the set up and execution of the Monte Carlo simulations of flood events in Carlisle.

Table 8.2. Model parameters for hydraulic flood simulations of Carlisle, UK.

Parameter	Description	Full range used
<b>Peak discharge at Sheepmount</b>	Peak discharge for the River Eden at the location of the Sheepmount gauging station. Values selected from the flood frequency curve derived in chapter 6.	573 - 3395 m <sup>3</sup> s <sup>-1</sup>
<b>Peak discharge at Cummersdale</b>	Peak discharge for the River Caldew at the Cummersdale gauging station. Values selected from Neal et al. (2012).	10 – 424 m <sup>3</sup> s <sup>-1</sup>
<b>Peak discharge at Harraby Green</b>	Peak discharge for the River Petteril at the Harraby Green gauging station. Values selected from Neal et al. (2012).	13 – 465 m <sup>3</sup> s <sup>-1</sup>
<b>Eden flood duration</b>	The width (in hours) of the simulated triangular flood hydrograph for the River Eden. The hydrograph widths for the Rivers Caldew and Petteril were set to 66% and 94% of the Eden hydrograph width respectively.	1 – 100 hours
<b>Cummersdale to Eden lead time</b>	The time (in hours) by which the peak discharge for the River Cummersdale precedes the peak discharge for the River Eden.	0 – 7 hours
<b>Petteril to Eden lead time</b>	The time (in hours) by which the peak discharge for the River Petteril precedes the peak discharge for the River Eden.	0 – 7 hours
<b>Channel roughness (<math>n_{ch}</math>)</b>	From behavioural parameter sets (see chapter 5)	0.047 – 0.090 m <sup>1/3</sup> s <sup>-1</sup>
<b>Floodplain roughness (<math>n_{fp}</math>)</b>	From behavioural parameter sets (see chapter 5)	0.032 – 0.090 m <sup>1/3</sup> s <sup>-1</sup>

It is not the intention of this research to identify areas of very high flood risk (for example 0.1 AEP), so the number of simulations can be reduced by only running simulations where the AEP for at least one of the rivers was 0.05 or less (return period of 20 years or more). This ensures that for each of the 100 sets of 1,000 year flood events, the top 50 floods for each river were simulated. The spatial dependence described in section 8.2 meant that often a single simulation contained 'top 50' floods from more than one river. Overall, of the 100,000 possible simulations, 10,544 needed to be run to capture all the top 50 floods on the three rivers. These simulations were all run twice using different digital elevation models (DEMs) for Carlisle.

The first set of simulations were run with the DEM including the flood defences that are in place currently (see chapter 2 for details), then the simulations were run again using a DEM without the recent flood defences. The results of the simulations run with the flood defences in place will provide estimations of the actual, current flood risk in the study area, which is extremely relevant to residents and insurers, whereas the simulation results without flood defences show the underlying flood risk which must be considered for planning and development purposes (DETR, 2001b). Additionally, running the simulations both with and without the flood defences gives an indication of the benefit provided by those defences. In these estimates of flood risk and uncertainty, no attempt is made to simulate failure of any of the flood defences in Carlisle.

At the time of writing the defences in Carlisle are all assumed to be in good condition (Environment Agency, 2009a). However a full uncertainty analysis of flood risk should take account of the likelihood and consequences of possible flood defence failure (see for example Apel et al., 2009b). Table 8.3 summarises the process of preparing all 10,544 simulations.

Table 8.3. Steps in preparing and running the Monte Carlo simulations of the sets of 1,000 years flood simulations for Carlisle

Task	Description	Repetition
<b>Generate 100 sets of 1,000 year flood events</b>	Use the Caldew and Petteril peak discharges from Neal et al. (2012). Generate the Eden discharges using the posterior distributions for the generalised extreme value distribution parameters derived in chapter 6.	Once with DEM with current flood defences, once with DEM without defences.
<b>Identify top floods</b>	Select all events where at least one river experiences a 0.05 AEP flood or worse.	Once for each of the 100 sets generated in task 1
<b>Generate flood hydrographs</b>	Generate triangular ‘design’ hydrographs for each river based on the peak discharge and a randomised duration. Select random lead times for the Caldew and Petteril flood waves.	For all 10,542 simulations
<b>Select ‘behavioural’ parameter set</b>	Randomly select a parameter set ( $n_{ch}$ and $n_{fp}$ ) according to the weight applied to the parameter sets.	For all 10,542 simulations
<b>Create files required to run LISFLOOD-FP</b>	Parameter file, file containing flood hydrographs.	For all 10,542 simulations
<b>Run simulations</b>	Run as tasks as jobs on Condor parallel computing environment at the University of Bristol (2014).	For all 10,542 simulations

## 8.6 Model sensitivity

Establishing the role of individual sources of uncertainty in the overall uncertainty of flood risk in the study area is desirable as a guide to which sources of uncertainty can be safely ignored and which require the most attention (see for example Apel et al., 2008; Merz and Thielen, 2009; Pappenberger et al., 2006a; 2006b; Saint-Geours et al., 2013). In chapter 5, the first order sensitivity of the hydraulic flood model of the January, 2005 to the 5 model parameters was examined using the method of Sobol' (Saltelli et al., 2000). In this case the hydraulic model is only one part of the model chain. Therefore it is not straightforward to elicit the sensitivity of model chain to the various parameters. For example, the selection of model parameters for the variance based sensitivity analysis used in chapter 5 should employ a random or pseudorandom sampling strategy such as a Latin hypercube, but in this chapter some parameters are sampled from probability distribution functions which are the output of earlier steps in the modelling chain. Notwithstanding these issues, some useful information about the model's sensitivity can still be garnered.

In order to analyse the sensitivity of the model to the parameters, some way of expressing the model output as a single value is required. Unlike in chapter 5 where the model could be scored against data from a real event, here a scoring method is designed that gives a simple metric of the destructiveness of each simulated flood event. The measures described in the results section (8.8) that evaluate the risk to population and property are inappropriate for this task because not all the steps required to calculate them can be automated. Instead, a cruder method of evaluating the flood severity is used based on CORINE 2006 land cover data (EEA, 2006). A similar approach was employed by Jongman et al. (2012) when comparing flood damage models. The 100 m x 100 m resolution CORINE data was re-sampled to match the 10 m x 10 m model resolution. Each model square was given a weighting depending on its CORINE land cover designation (table 8.4):

Table 8.4. CORINE land cover (CLC) categories with weightings used for model scoring.

CLC Code	Description	Weighting
111	Continuous urban fabric	2
112	Discontinuous urban fabric	1
121	Industrial or commercial units	1
122	Road and rail networks and associated land	1
	All other CLC codes	0

The inflated weighting allocated to areas of ‘continuous urban fabric’ is based on the assumption that the consequences of a flood in these areas are greatest. Note that the score defined here is only proposed as a rough metric for use in the sensitivity analysis. For each flood simulation, the score for each 10 m x 10 m pixel is the multiple of the maximum water depth simulated at that pixel multiplied by the weighting for the CLC code for the pixel. The score for all pixels in the study area is summed to give a single value per flood simulation. In this way, flooding in area where there is no development does not contribute to the score but flooding in areas of ‘continuous urban fabric’ contributes the most.

Comparing the scores for all 10,542 simulations will be uninformative because of the range of peak flood discharges. Instead the sensitivity analysis was limited to only those simulations where the peak discharge of the River Eden at the location of the Sheepmount gauging station was within the uncertainty bounds of the 0.01 AEP flood as estimated in chapter 6 ( $1177 - 1631 \text{ m}^3\text{s}^{-1}$ ). The method described in chapter 5 to ascertain the approximate first order sensitivity of the model to the parameters was then applied to the reduced set of 2,528 simulations. Saltelli (2002) recommends  $2n(k + 1)$  simulations where  $n$  is the sample size ranging from 100 to 1,000 and  $k$  is the number of model parameters. In this case  $k = 8$ , so the 2,528 simulations give an

effective sample size ( $n$ ) of 140, which is within the range specified by Saltelli. The results of the sensitivity analysis can be seen in table 8.5.

It is clear from table 8.5 that the peak discharge at Sheepmount, which is representative of the overall quantity of water entering the study area across the three main rivers, has the biggest impact on model performance. Unlike the results of the sensitivity analysis in chapter 5, where the channel roughness was the most significant parameter, here it has a much lesser impact than the discharge. The Eden flood duration parameter (from which the duration on the other rivers are derived) seems not to have a significant impact on the model performance, although it should be noted that the flood duration is deliberately correlated with the flood peak, so a first order sensitivity analysis like this will not correctly show the impact of these related model parameters.

Table 8.5. Sensitivity index of the flood model with peak discharge of the River Eden restricted to between  $1177 \text{ m}^3\text{s}^{-1}$  and  $1631 \text{ m}^3\text{s}^{-1}$ .

Parameter	First order sensitivity index
Peak discharge at Sheepmount	0.258
Peak discharge at Cummersdale	0.051
Peak discharge at Harraby Green	0.074
Eden flood duration	0.022
Cummersdale to Eden lead time	0.005
Petteril to Eden lead time	0.001
Channel roughness ( $n_{\text{ch}}$ )	0.081
Floodplain roughness ( $n_{\text{fp}}$ )	0.008

## 8.7 Results

### 8.7.1 Deterministic estimates of flood risk

The 10,542 simulation results can be thought of either as 100 separate 1,000 year simulations which provide information about the flood risk uncertainty up to a return period of one thousand years (0.001 AEP), or as a single time series simulation of 100,000 years of floods that can be used to give deterministic estimates of flood risk for higher return periods. A flood risk map for the city can be created by examining each of the 10,542 simulation results and, for each 10 m x 10 m pixel, keeping a score of the number of times the pixel is 'flooded'. By dividing the scores for each pixel by 100,000, the resulting map will be a representation of the AEP for the study area. While the map will not resolve flood risk detail in areas of very high flood risk (since only events where one of the three rivers experienced a 0.05 AEP or worse were simulated), it does provide a reliable estimate of those areas subject to fluvial flood risk between 0 and 0.033 AEP. Figure 8.5 shows the flood risk map for Carlisle both with the current defences in place (a) and with the defences removed (b). The flood risk areas in figure 8.5 can be compared against figure 8.6 which shows the equivalent flood zones as defined by the Environment Agency (2011b). Note that figures 8.5 and 8.6 are deterministic representations of flood risk and do not contain any estimate of uncertainty. Figure 8.5a shows that using this model, the flood defences seem to provide adequate protection against a 0.01 AEP flood except in the area near the downstream boundary. Rather than necessarily indicating insufficiency in the flood defences in this area, it might indicate a problem with the model's downstream boundary conditions. The LISFLOOD-FP model was configured to assume a uniform flow along the downstream boundary with the water surface slope set at  $6 \times 10^{-4} \text{ m m}^{-1}$  to match the valley slope. A similar downstream boundary set up was used by both Horritt et al. (2010) and Neal et al. (2012) who point out that it may cause backwatering effects downstream of the location of the Sheepmount gauge. The problem is exacerbated by the lack of observational data in that area from the January 2005 flood (see figure 4.2) which would render it largely futile to attempt to tune the downstream boundary conditions as part of the hydraulic model calibration.



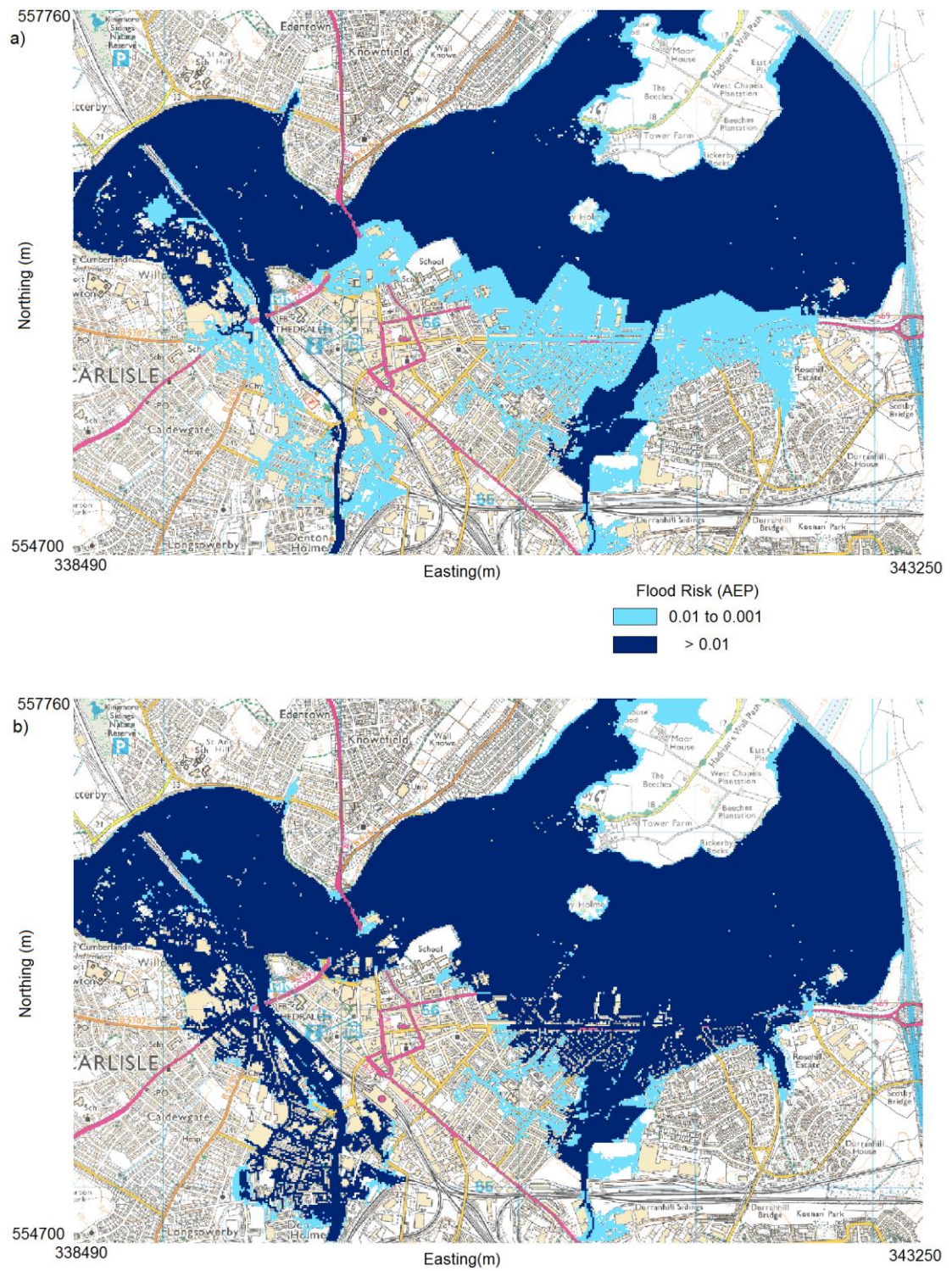


Figure 8.5. Estimates of flood risk for Carlisle (a) with the current flood defences in place and (b) with flood defences removed. Background map © Ordnance Survey Crown copyright.

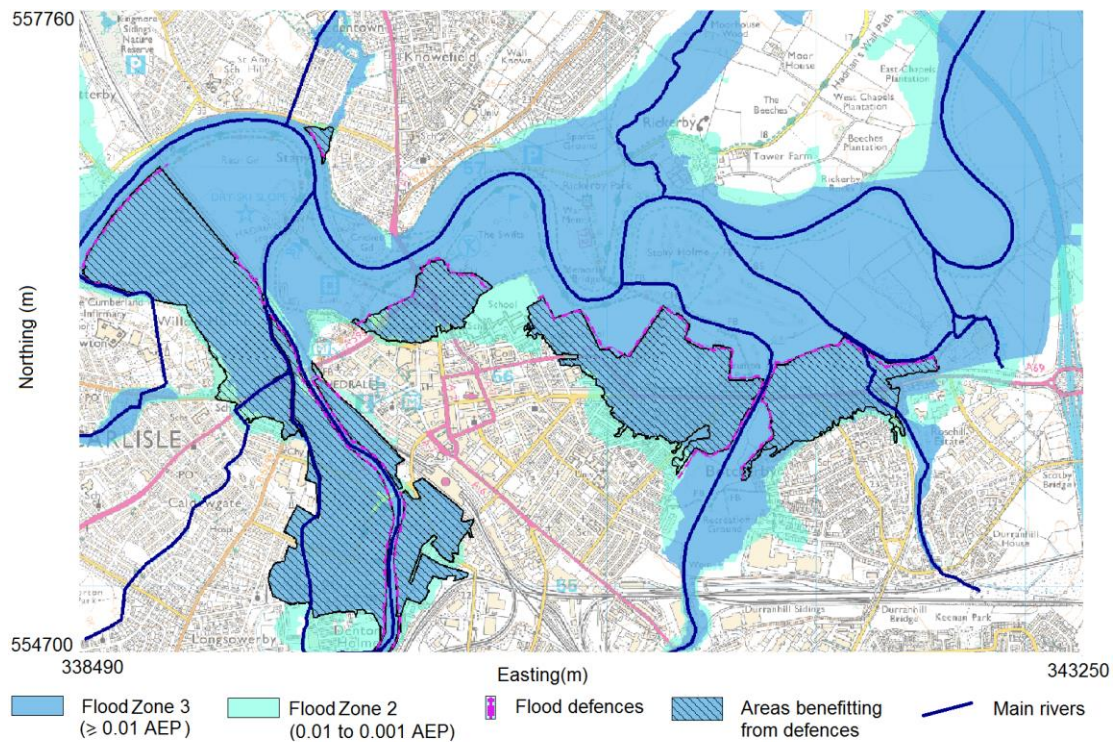


Figure 8.6. Environment Agency flood map for planning showing fluvial flood risk zones 2 (0.01 to 0.001 AEP) and 3 (AEP 0.01 or greater) (DETR, 2001b). The flood risk zones shown refer to the probability of river flooding, ignoring the presence of defences (Environment Agency, 2011d). Contains Environment Agency information © Environment Agency and database right. Background map © Ordnance Survey Crown copyright.

### 8.7.2 Uncertainty in flood risk estimates.

The uncertainty in the estimates of flood risk was quantified by examining the differences in flood risk indicated by the 100 sets of 1,000 year flood simulations. For each of the 1,000 year flood simulations, a different extent of the 0.01 AEP flood is given by noting all the pixels in the study area that are inundated at least 10 times. From this the uncertainty in the 0.01 AEP flood is represented for each pixel by the number of times that pixel is included in the 0.01 AEP flood extent across all 100 sets of 1,000 year flood simulations. In this way each pixel is assigned a probability between 0 and 1 of whether it is within the 0.01 AEP flood extent.

Attempting to quantify the uncertainty using only 100 samples is not ideal, so no attempt was made to establish PDFs of the flood risk for individual pixels in the study



area or even to give reliable estimates of the 95% confidence limits. Instead the 90% confidence limits of the design 0.01 AEP flood were identified, and for all the pixels within the confidence limits, each pixel is allocated a probability of inundation by the 0.01 AEP flood of low (0.05 to 0.35), medium (0.35 to 0.65) or high (0.65 to 0.95). Figure 8.7 show the uncertainty in the 0.01 AEP flood both with (a) and without (b) the flood defences.

The large areas of yellow (low probability of inundation by a 0.01 AEP flood) in figure 8.7a shows that, even though the defences in Carlisle are designed to withstand floods up to 0.005 AEP (Environment Agency, 2009a), the uncertainties associated with flood frequencies mean there is a (low) chance that a 0.01 AEP event will overtop the defences and cause serious inundation.

### 8.8 Consequences of uncertainty – risk to property and population

The probabilistic flood maps of a design flood can be used to assess the consequences of flooding from the aspects of those likely to be affected, known as the receptors of the hazard (Sayers et al., 2002). By examining the intersection of probabilistic flood maps with map layers containing detailed information on hazard receptors, such as population, property, infrastructure or assets with particular vulnerability to flooding it is relatively straightforward to quantify risk in terms of absolute numbers within the area at risk of flooding. But additional links in the modelling chain may be needed to produce useable estimates of flood risk as defined by the likelihood of the hazard multiplied by the consequences.

In this section an attempt is made to quantify the uncertainty in the 0.01 AEP flood in terms of the number and type of properties at risk in Carlisle. The following chapter then deals with the consequences for planning regulations and the availability of insurance, of defining flood zones deterministically in terms of AEPs.

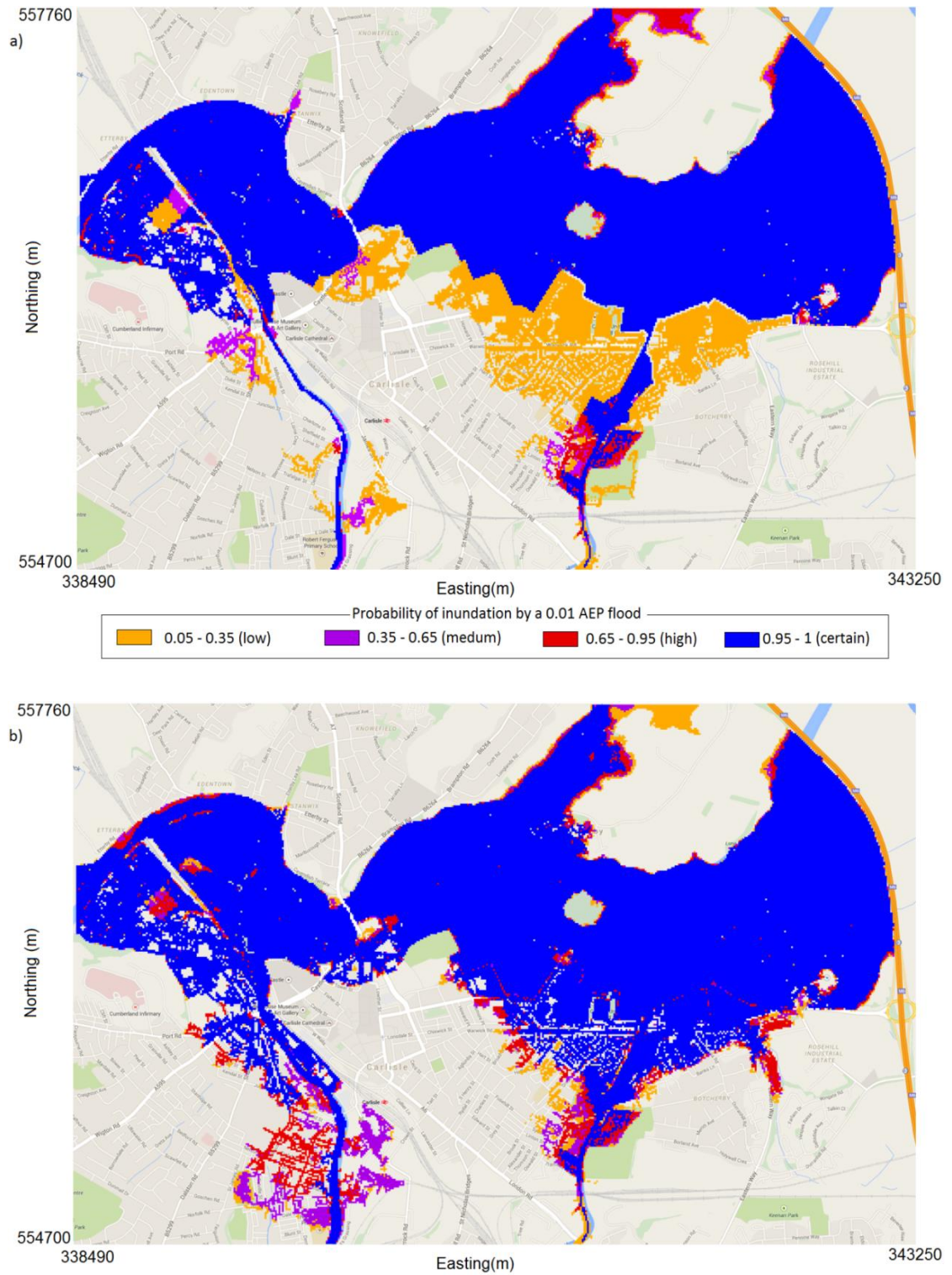


Figure 8.7. Uncertainty in 0.01 AEP flood for Carlisle (a) with the current flood defences in place and (b) with flood defences removed. Map data © 2014 Google.

The data for Carlisle from the National Receptor Dataset includes accurate coordinates of building locations. All buildings that overlap with pixels where it is uncertain if they are within the 0.01 AEP flood extent were identified and can be seen in figure 8.8. The building colour represents the likelihood of the building being inundated by a 0.01 AEP flood. Figure 8.8 does not give any indication of the depth of water, just whether or not they will remain dry.

The uncertainty information for the 0.01 AEP flood can be combined with data from the National Population database (NPD) (Smith and Fairburn, 2008) to give confidence limits for the local population at risk from the 0.01 AEP flood. Using the estimates for occupancy of residential homes from the NPD, the risk to the population is summarised in table 8.6

The figures in table 8.6 give an indication of the extent of the 0.01 AEP flood in terms of the number of buildings that may be affected directly by the flood water. The Environment Agency estimates the population at risk from a 0.01 AEP flood to be approximately 6,500 (Environment Agency, 2009a) which is very close to the estimate of 'usual or night time' population at risk from table 8.6 calculated by adding the numbers from the 'high' and 'certain' columns in the 'with flood defences removed' section (6,372). In order to obtain more information on the damaging effects of the flood it is necessary to take account of the possible range of depths affecting the properties.

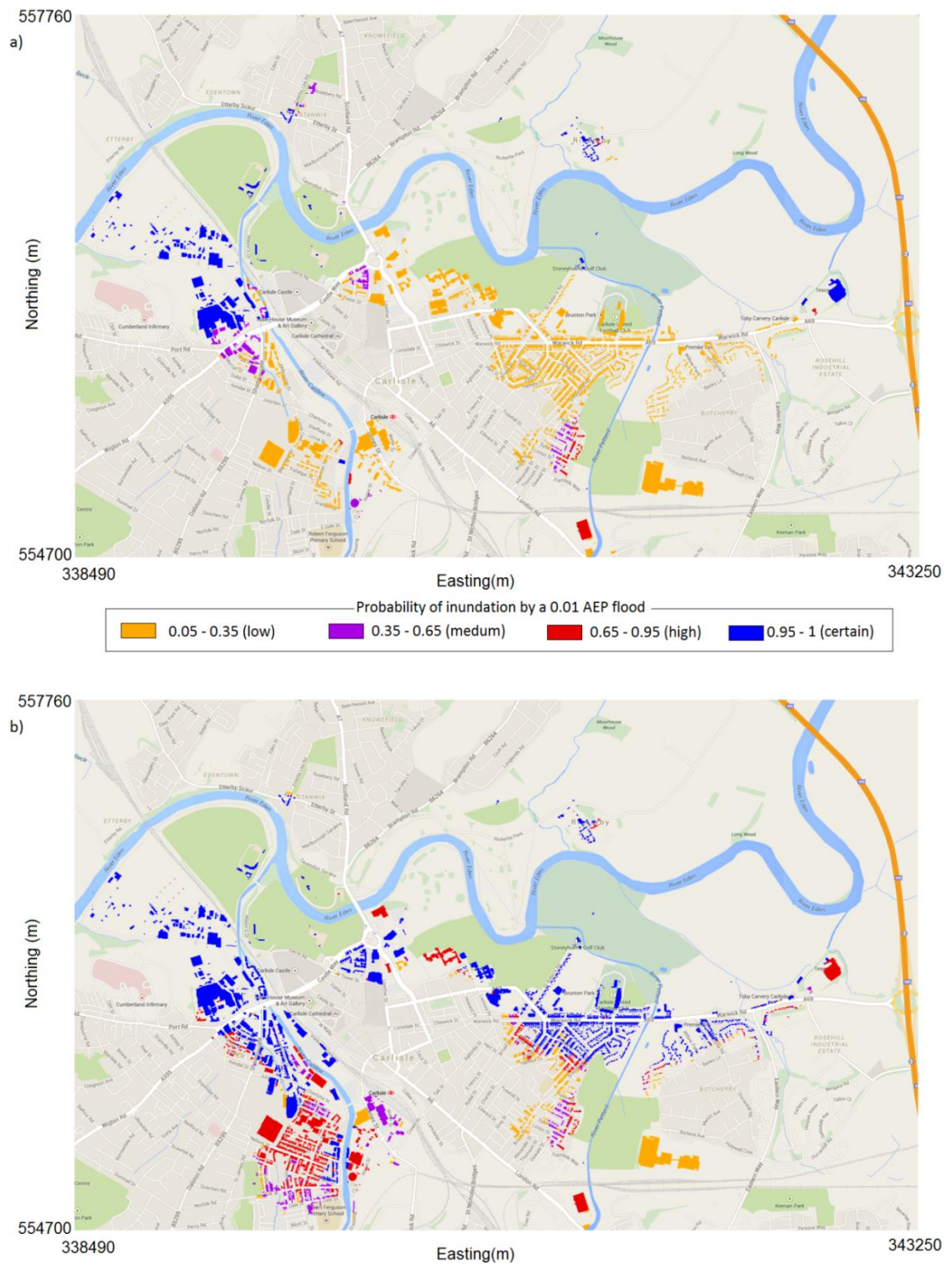


Figure 8.8. Buildings affected by the uncertainty in the 0.01 AEP flood extent, (a) with the current flood defences in place and (b) with flood defences removed. Map data © 2014 Google.

Table 8.6. Summary of residential properties and population at risk from 0.01 AEP flood in Carlisle.

	Probability of inundation by a 0.01 AEP Flood				
	0.05 – 0.35 low	0.35 – 0.65 medium	0.65 - 0.95 high	0.95 - 1 certain	Total
<b>With current flood defences in place</b>					
<b>Residential properties</b>	2,558	219	114	293	3,184
<b>‘Usual or night time’ population.</b>	5,557	386	214	555	6,712
<b>Day time population, term time.</b>	2,143	159	85	227	2,614
<b>Day time population, non-term time.</b>	2,764	188	104	269	3,325
<b>With flood defences removed</b>					
<b>Residential properties</b>	523	554	1,143	1,938	4,158
<b>‘Usual or night time’ population.</b>	1,134	1,066	2,260	4,112	8,572
<b>Day time population, term time.</b>	430	421	886	1,640	3,377
<b>Day time population, non-term time.</b>	528	527	1,132	2,053	4,240

## 8.9 Financial risk

Estimating the cost in financial terms of a flood is fundamental to the benefit-cost analysis and prioritisation of investment in flood defence schemes as well as providing guidance in many other areas of risk analysis (Merz et al., 2010). The benefits of a scheme as calculated from the average annual damages (AAD) using a loss-probability curve involved estimating the cost of several floods of different likelihoods. In the UK, publications called the Multi-Coloured Manual and the shorter Multi-Coloured Handbook (MCH) from the Flood Hazard Research Centre (FHRC) at Middlesex University are recommended for use in cost benefit analysis of flood risk management

schemes (Penning-Rowsell et al., 2013; Penning-Rowsell et al., 2010). The MCM and MCH and accompanying spreadsheets provide depth-damage tables of average costs of floods of certain depths across different categories of domestic and commercial property types.

The MCM method works on a micro-scale where losses are calculated for each individual property at risk, other comparable models include 'Flood Loss Estimation Model' (FLEMO) from the German Research Centre for Geosciences (Thieken et al., 2008) and the HAZUS-MH used to estimate the effects of many natural hazards in the US (FEMA, 2009). Meso-scale damage models work at a lower resolution in conjunction with land-use data rather than databases of individual properties, examples include Damage Scanner in use in the Netherlands (de Moel et al., 2011) and a pan-European model developed by the European Commission's Joint Research Centre - Institute for Environment and Sustainability (Huizinga, 2007). The models mentioned here and the many others in use throughout the world all count water depth as the primary agent of flood damage (Yu et al., 2013), but many make use of factors such as contamination, debris, velocity, rate of inundation and flood duration which are all known to influence the costs of flooding (Förster et al., 2008; Gissing and Blong, 2004; Kelman and Spence, 2004; Merz et al., 2010).

For the UK, the MCH provides deterministic depth damage estimates for different house and business types. However, although predecessors to the MCH included 95% confidence limits (Penning-Rowsell and Chatterton, 1986), they are not produced for subsequent versions (Beven et al., 2011 p.25). The depth damage tables in the 2010 MCH were used, with the maximum simulated flood depths, to assess the range of financial costs of floods with four different annual exceedance probabilities in Carlisle both with the current flood defences in place and with the defences removed (see table 8.7). Even without the uncertainty in the depth-damage estimates included, the uncertainty bounds are very wide for the larger floods. This is particularly true for the 'with defences' scenarios when uncertainty over whether or not the defences will be overtopped results in the maximum damage estimate being more than an order of magnitude above the minimum. For comparison purposes, Jongman et al. (2012) estimate the cost of the January, 2005 flood at £383m (2005 prices).



Table 8.7. Summary of financial risk in Carlisle. Values are averages between the estimates for short duration (less than 12 hours) and long duration flood events as defined in Penning-RowSELL et al. (2010). 2010 prices, £m.

AEP	30	0.01	0.003	0.001
(return period, years)	(0.033)	(100)	(333)	(1,000)
Property Type	Estimated damage (90% confidence interval)			
With current flood defences in place				
Residential	3.44 (1.92 - 78.9)	15.3 (2.82 – 114)	44.6 (3.44 – 176)	74.6 (3.77 – 224)
Non-Residential*	13.9 (1.77-34.5)	46.5 (28.6 -143)	75.6 (25.9 – 221)	109 (33.7 – 281)
Total	17.4 (3.69 – 41.4)	61.7 (31.4 – 258)	176 (29.3 – 369)	183 (37.5 – 505)
With flood defences removed				
Residential	49.0 (25.3 – 90.9)	70.3 (38.4 – 127)	93.6 (44.7 – 183)	111 (55.2 – 213)
Non-Residential*	78.4 (50.2- 125)	96.4 (60.5 - 162)	118 (66.1 – 224)	138 (77.0 – 259)
Total	127 (75.6 – 215)	167 (98.9 – 290)	212 (111 – 407)	250 (132 – 472)

\* Depth damage tables are not provided for all non-residential properties. Examples include bus stations (the Stagecoach bus depot in Carlisle was flooded in January, 2005 costing the company over £3m (The Cumberland News, 2005)) and football grounds (Brunton Park, the home of Carlisle United FC also flooded in January, 2005 forcing the club to play their 'home' games at Morecombe for the next six weeks).

## 8.10 Discussion

The wide range of damage estimates shown in table 8.7 give an indication of the difficulties in estimating the financial impacts of flooding. Furthermore, although considerable lengths have been taken in this and the preceding chapters to account for many sources of uncertainty, not all have been included. To understand the issue of uncertainty in environmental modelling it is helpful to think in terms of aleatory (stochastic) and epistemic natures of the various sources of uncertainty (Beven, 2008; Merz and Thielen, 2005; Refsgaard et al., 2007; Rougier and Beven, 2013; Walker et al., 2003). It is the aim of the environmental modeller to minimise the epistemic uncertainties through greater understanding of the physical processes and more accurate data leaving a probabilistic characterisation of the aleatory uncertainty (Merz and Thielen, 2009). However, as discussed in previous chapters, the need for risk managers to act with imperfect information and the complicated interactions between sources of uncertainty may require a pragmatic, imprecise approach to representing epistemic uncertainties probabilistically (Beven et al., 2014). Table 8.8 gives an extensive list of the factors that contribute to uncertainty when quantifying flood risk and its consequences with comments on the aleatory and epistemic components.

### 8.10.1 Benefit-cost analysis in Carlisle

One of the significant applications of estimates of financial risk is to inform cost benefit analysis and prioritisation of investment in the construction and maintenance of flood defence schemes. Although Carlisle had several schemes already in place prior to 2005 (Atkins, 2011), the extent and damage of the January 2005 flood was such that there was significant political pressure on the Environment Agency to greatly improve the flood protection of the city (BBC News, 2005). However, before money can be spent on flood defence projects, a project appraisal report must first establish that the project will bring benefits that exceed the construction and maintenance costs over the lifetime of the scheme (Defra, 2009). Additionally, if there are several competing schemes for the area in question, the report must decide which scheme provides the best value for money. The guidance for completing a project appraisal report is lengthy and detailed, covering all aspects of accounting methods to be used including discount rates to apply to convert future costs to present values (see Environment Agency

(2010a), document FCERM-AG for full details). A key step in the appraisal process is to estimate the average annual damages (AAD) from flooding in the study area using a loss-probability curve, which is a graph of flood probability against estimated damage

Table 8.8. Summary of main sources of aleatory and epistemic uncertainty when quantifying flood risk and its consequences.

Uncertainty source	Quantified	Comments
<b>Hydraulic model</b> <ul style="list-style-type: none"> <li>- <b>Parameters</b></li> <li>- <b>Structure</b></li> <li>- <b>Boundary conditions</b></li> <li>- <b>Calibration data</b></li> </ul>	Yes	Uncertainty estimated using GLUE methodology in chapter 5.  See Beven and Binley (1992); Beven (2006); (2008) for descriptions of GLUE.  See Mantovan and Todini (2006) and Stedinger et al. (2008) for criticism of the GLUE methodology.
<b>Hydraulic model limitations</b> <ul style="list-style-type: none"> <li>- <b>Flooding from non-fluvial sources</b></li> <li>- <b>Blockage effects by debris</b></li> <li>- <b>Conveyance within channel</b></li> <li>- <b>Downstream boundary</b></li> </ul>	No	Model calibrated on a single, real event, but scaled to represent a continuum of hypothetical events.  Some hydraulic models can model flooding from all sources and allow blockage simulation (interview, Associate Technical Director, engineering company).  Channel conveyance is known to vary greatly with seasonality. During the summer, growth of riparian vegetation can greatly reduce channel conveyance (Knight et al., 2010).
<b>DEM representing floodplain topography</b>	Partially	Partially captured by GLUE analysis.  Hydraulic model run at 10 m resolution horizontal resolution. Vertical uncertainty estimated at 0.18 m by (Mason et al., 2007b). The vertical DEM uncertainty will have a significant impact on damage estimate when considering building threshold heights.

Uncertainty source	Quantified	Comments
<b>Uncertainties in flood frequencies</b> <ul style="list-style-type: none"> <li>- Short time series</li> <li>- rating curve errors</li> <li>- historical discharge estimates</li> </ul>	Yes	<p>Incorporated in Bayesian statistical model.</p> <p>The flood frequency curve represents the aleatory element of the flood risk management. Confidence limits represent the epistemic uncertainty.</p>
<b>Flood Frequency curve</b> <ul style="list-style-type: none"> <li>- choice of extreme value distribution</li> <li>- non-stationarity</li> </ul>	No	<p>See Wood and Rodríguez-Iturbe (1975); Apel et al (2008) for ways to define composite extreme value distributions.</p> <p>See Pattison and Lane (2011); Stedinger and Griffiths (2011); Pattison et al. (2012); Prosdocimi et al. (2014) for consideration of non-stationarity and climate change in flood frequencies.</p>
<b>Spatial dependence between river flows</b>	Yes	Method of Neal et al. (2012) used.
<b>Hydrograph shape &amp; lead times of peak flows</b>	Yes	<p>Triangular hydrographs of varying widths simulated. Differing lead times of tributaries simulated.</p> <p>Uncertainty in hydrograph shape, duration and timing will contain aleatory and epistemic elements.</p>
<b>Flood defences</b> <ul style="list-style-type: none"> <li>- Errors in crest heights</li> <li>- Possibility of failure</li> <li>- Lack of maintenance of culverts etc.</li> </ul>	No	<p>Breaches of defences and culvert blockages by debris may be primarily random (aleatory) or have an epistemic element when the condition and maintenance of the defence is considered.</p> <p>Failures may be the result of breaches caused by overtopping (for example Apel et al., 2009b; 2008), breaches caused by structural failure due to poor design or lack of maintenance (Hall et al., 2005b) or blockages</p>

Uncertainty source	Quantified	Comments
		of culverts or other water courses (Venables, 2013). When considering the possibility of the failure of a dam, the consequences are so severe that these events are generally given special consideration (Singh, 1996).
<b>Damage estimation</b>	No	Errors in property information databases e.g. finished floor levels not considered.
- <b>Properties affected</b>		
<b>Damage estimation</b>	No	Numbers in the National Population Dataset are statistical averages, so are subject to aleatory and epistemic uncertainty.
- <b>Population affected</b>		
<b>Damage estimation</b>	Partially	Range of possible flood depths considered when estimating financial risk. Errors in building thresholds and finished flood levels not captured.
- <b>Inundation depth</b>		
- <b>Flood duration</b>		
- <b>Flow velocity</b>		Short and long damage estimates calculated.  Flow velocity not considered.
<b>Damage estimate</b>	No	Depth-damage tables in the MCM are statistical averages and are subject to both aleatory and epistemic uncertainty. See section 8.10.2 for a discussion of uncertainties in flood damage modelling.
- <b>Depth-damage curves</b>		

Figure 8.9 shows an example of an idealised loss-probability curve. In figure 8.9, the area under curve A is the AAD due to flooding in the scenario where no additional flood defences are in place. Curve B is a proposed flood defence scheme that provides a standard of protection (SOP) of 0.005 AEP, consequently curve B stays very close to the y axis for AEP above 0.005, but rapidly rises for AEP below 0.005 because more extreme floods will overtop the defences designed to withstand a 0.005 AEP event. Curve C is a defence structure that provides protection to 0.01 AEP. The benefit of

proposed scheme B is therefore the area under curve A minus the area under curve B (the residual damages), this is the area shaded grey in figure 8.9. The benefit of scheme B, having lower residual damages, is greater than that of scheme C, but scheme B is likely to cost more than scheme C.

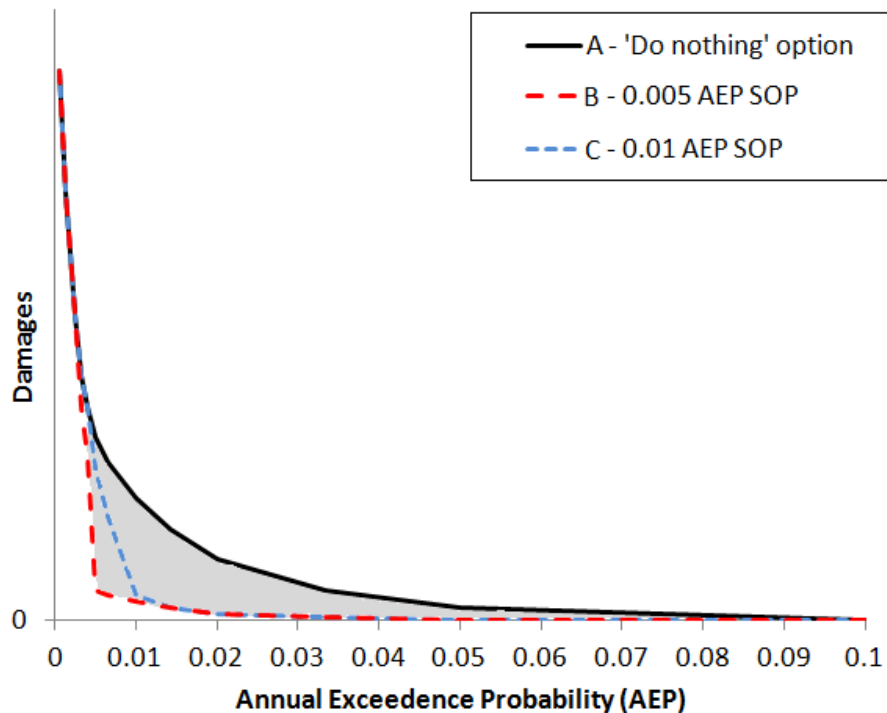


Figure 8.9. Example loss-probability curves, showing three scenarios: A – ‘do nothing’, B, provide a standard of protection (SOP) up to 0.005 AEP, and C – provide a SOP up to 0.01 AEP.

In reality the loss-probability curves may look nothing like the rather idealised examples shown in figure 8.9. The curves do not adhere to a mathematical formula, so need to be generated by calculating individual points and interpolating between those points. The appraisal guidance from the Environment Agency (2010a p. 214) recommends calculating 5 points (minimum of 3) and drawing a straight line between the points to complete the ‘curve’ (Environment Agency, 2010a). This introduces yet another source of uncertainty to the cost benefit analysis (Ward et al., 2011).

The uncertainty in the loss-probability curves means the practitioner executing the benefit-cost analysis is likely to be faced with making decisions based on incomplete knowledge (CIRIA, 2013; Environment Agency, 2009d; Hall and Harvey, 2009). Figure

8.10 shows the loss probability curves (including uncertainty) for Carlisle using the figures from table 8.7. Figure 8.10 shows considerable overlap between the confidence limits of the two loss-probability curves, suggesting greater complexity in the estimation of the benefits of a flood alleviation scheme. However, it should be noted that there will be a strong correlation between the errors in the loss-probability curves, and that the guidance for scheme appraisal is aimed at making a choice, not reducing uncertainty in the estimated benefits of the proposed schemes (Environment Agency, 2010a p. 17).

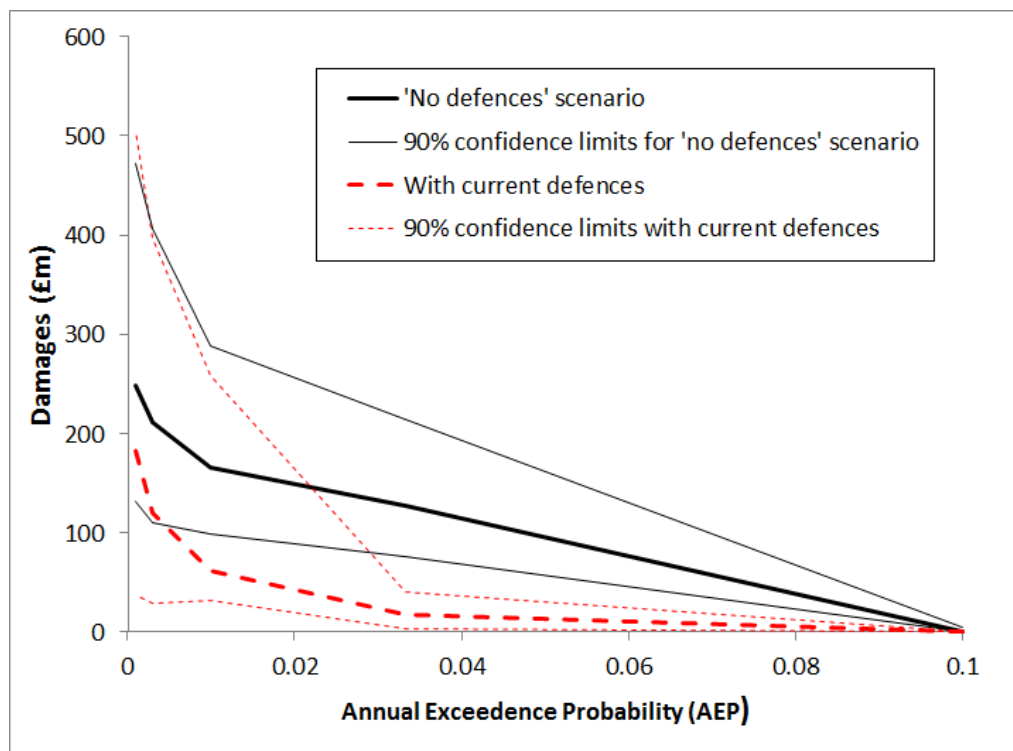


Figure 8.10. Loss-probability curves with confidence limits for Carlisle, showing the loss-probability curves with the current defences in place and the 'no defences' scenario.

If the economic benefit-cost ratio is much greater than unity, then the scheme is more likely to be approved even if there is considerable uncertainty in the calculation of the benefits. For example, the project to improve the defences in Carlisle to a 0.005 AEP SOP subsequent to the January, 2005 flood achieved a benefit-cost ratio of 8.6 (Environment Agency, 2007 p. 3); well above the median for nationally funded schemes which is approximately 3 (Ministry of Agriculture Fisheries and Food, 1999). In

the following section the important issue of uncertainty in the consequences of flooding due to the method of damage estimation is examined.

#### 8.10.2 Uncertainty in flood damage modelling

For the purposes of the Carlisle example in this chapter, only one method of estimating the financial cost of flooding was used. The motivation for this decision was a matter of scope rather than an assumption that damage estimates are in any way insensitive to the estimation methods used or that the magnitude of the uncertainty is insignificant compared to other sources of uncertainty. Indeed studies that have compared multiple flood damage models suggest a huge variation in modelling approaches which represent perhaps the largest source of uncertainty in the overall assessment of flood risk (Apel et al., 2008), yet more attention is typically paid to the hazard rather than the damage aspect of flood risk assessment (Merz et al., 2010).

The Multi-Coloured Manual (MCM) damage estimation model was applied on a micro-scale in this project. I.e. damage estimates were made by applying the MCM methods at an individual property level using the data in the National Receptor Dataset (Environment Agency, 2011e). It is not always possible or advisable to take this approach and many flood damage models are applied at a meso-scale using lower resolution property data typically combined with land use datasets such as CORINE land cover data (EEA, 2006). Jongman et al (2012) compared, at the meso-scale, seven damage models used across Europe including the Multi-Coloured Manual from the UK. They found a variation in function uncertainty of a factor of 10.5 for their Carlisle case study. In their case study in the south of the Netherlands, de Moel and Aerts (2011) conclude that damage estimates are likely to vary by a factor of 5-6, but this is based on only three damage models compared to the seven used by Jongman et al. (2012). In order to keep depth-damage uncertainty within a probabilistic framework, Saint-Geours et al. (2013) represent uncertainty by applying a uniform PDF of -50 % to +50 % around a single set of depth-damage curves.

The comparative studies mentioned above all focus on inundation depth as the agent of damage. Whilst depth is generally recognised as the primary damage indicator (Yu et al., 2013), a host of other factors such as water velocity, contaminants,



debris, flood duration, sediment and season all affect damage to buildings property and agricultural land (Förster et al., 2008; Gissing and Blong, 2004; Kelman and Spence, 2004; Merz et al., 2010). In addition societal factors can have a significant effect in certain circumstances: flood preparedness either in the form of warnings (Demeritt et al., 2013); awareness campaigns or recent experience of flooding (Thieken et al., 2007). In Germany, Cologne was affected by floods of similar magnitudes in 1993 and 1995 but the damage due to the second flood was approximately 50% lower than the first (Merz and Thieken, 2009).

### 8.11 Conclusion

In this chapter the results of the modelling chain built for representing the uncertain 0.01 AEP design flood in Carlisle make the best use of the data available. A deterministic assessment of the results is not inconsistent with the Environment Agency's estimates of flood risk in this area (see figures 8.5 & 8.6), but when the model uncertainty is included, the quantification of risk to property and population shows wide confidence intervals (section 8.8). The model shows greatest sensitivity to the total discharge into the study area and this is the most significant source of uncertainty when considering the hazard aspects of flood risk, i.e. the depth and extent of inundation. However, the uncertainty in the consequences of flood events, which has been discussed here but not quantified, is potentially greater than all other uncertainties. If one considers the uncertainty in flood risk as "only important if its resolution would make a difference to which option is chosen" (Penning-Rowsell et al., 2013) i.e. uncertainty is important when it may affect decisions required from policy-makers and other stakeholders, then agreement as to how to quantify the consequences of flooding must be paramount. In section 8.10.1 it was demonstrated how the results of the modelling chain might be used for benefit-cost analysis of flood protection schemes in Carlisle, but it seems there are still fundamental questions over what should be considered in terms of both the costs (Viavattene and Faulkner, 2012) and benefits (Defra, 2004a) of schemes. By taking a more generic view of the impact and communication of uncertainty within several policy areas, the next chapter will give additional context to the subject and attempt to address highly relevant questions such as how uncertainty affects policy decisions.

## Chapter 9. Implications of flood risk uncertainty for governance

### 9.1 Introduction

Chapters 4 to 8 have investigated and quantified some of the important sources of uncertainty that affect estimations of flood risk. Although methods have been proposed to reduce the uncertainty from some sources (observational data in chapter 4 and flood frequencies in chapter 6), there is no suggestion that it can be removed entirely to give deterministic evaluations of risk. While the previous chapters have showed that it is now possible to provide some quite detailed quantitative estimates of flood risk uncertainty, the purpose of this chapter is therefore to establish what the inevitable uncertainty means to policy-makers, managers, engineers and homeowners and how quantified uncertainty estimates might be used in the management and governance of flood risk.

Methods similar to those used in this project can produce objective figures of the numbers at risk and consequences of fluvial flooding, which are then put to use in many areas:

- Average annual loss estimates used by the insurance and reinsurance industries for setting premiums, and solvency risk regulation.
- Flood risk mapping for urban planning and flood forecasting for disaster response.
- Benefit-cost analysis for prioritisation of construction of defence assets.

Whilst assessing the cost of previous flood events is itself subject to huge uncertainty with estimates of the current annual economic risk for England and Wales between £0.25bn and £1.1bn (Penning-Rowsell, 2015), even the lower figure emphasises the importance of flood risk estimates to policy-makers and stakeholders in the areas listed above. By opening a dialog with representatives of public and private organisations concerned with flood risk, and establishing the extent to which uncertainty in flood risk is considered and managed across these policy areas it should

be possible to assess the relevance of this research to better align it with the future needs of public and private stakeholders.

The questions addressed in this chapter include...

- To what extent is the distinction between risk and uncertainty appreciated?
- How can uncertainty best be communicated amongst stakeholder?
- How does the acknowledgement of flood risk uncertainty affect...
  - Insurance premiums?
  - Planning decisions?
  - Allocation of resources to management of flood defence assets?

Although the Carlisle case-study was used as an example in the interview process and was sometimes referred to by the interviewees, the questions are asked primarily, but not exclusively in a UK-wide context.

The next section (9.2) provides background information on flood risk management in the UK in detail. Section 9.3 covers the methods employed whilst researching this chapter and lists the interview subjects. The research findings are detailed in section 9.4, then, in section 9.5 the results are discussed and comparisons made between the policy areas. The chapter concludes with a section containing some thoughts on the future directions for the management of uncertainty in flood risk estimates.

## 9.2 Background

### 9.2.1 Flood risk management

In the decades following the Second World War the responsibility for flood risk management (FRM) in the UK was heavily centralised in the hands of the government, with the emphasis initially on improving agricultural land through drainage (Penning-Rowse et al., 2006). Later, as the population grew and the pressure to develop on flood plains increased, the focus shifted to constructing structural defences to protect urban assets. This policy is epitomised by the ‘gentleman’s agreement’ in place between government and insurance industries between 1961 and 2003 (O’Neill and O’Neill, 2012) whereby insurance companies were obliged to provide insurance to flood prone properties on the understanding that the government would build and

maintain defences to an adequate standard to protect those properties (Johnson and Priest, 2008). But as the likely consequences of flooding were relentlessly driven up by continuing development on flood plains (Penning Rowsell and Wilson, 2006) and the possibility of increased flooding due to climate change (Schiermeier, 2011) there was a realisation amongst policy makers that it is not feasible to defend against all floods (Johnson et al., 2007).

The next three sections provide more detail on how quantitative risk estimates feature (in both setting standards and policy implementation) in the domains of insurance, land use regulation and planning, and the allocation process of for FCERM.

### 9.2.2 Insurance

In the post war years, England was one of the first countries to develop a private flood insurance scheme (Huber, 2004). Planners and policy makers placed little restriction on flood-plain development, a strategy driven by the confidence placed in the construction of hard defences and a flood-poor period between 1954 – 1990 (Crichton, 2012). Insurance for the new developments in areas at risk of flooding was provided on the basis of a “gentleman’s agreement” whereby the insurance industry and the state would share the responsibility of protecting the public from the hazard of flooding (Johnson and Priest, 2008). Under the terms of the agreement it was understood that the state would provide and maintain sufficient flood defences as well as controlling development in areas where flood prevention was impractical (O’Neill and O’Neill, 2012). For their part, insurers would provide affordable flood cover by making it a standard part of all household and small business insurance policies. By spreading the risk across all policy holders it was possible to offer low cost flood cover to all property holders except those where “continual, regular flooding was unavoidable” (Huber, 2004).

A series of damaging floods in the late 1990s stretched the “gentleman’s agreement” to breaking point, such that it was replaced by the “statement of principles” in 2003 (ABI, 2008; Johnson et al., 2007). The “statement of principles” is a voluntary agreement between members of the Association of British Insurers and the government; insurers pledged to continue to offer coverage to properties where the

annual probability of being flooded is 1 in 75 (1.3 %) or less, or where the Environment Agency has announced plans to reduce the annual risk to below 1.3 % within 5 years (Defra, 2008). Although, within the agreement premiums can vary to reflect differing flood risk, there is still heavy cross-subsidy from low to high-risk properties because flood coverage remains bundled with ordinary buildings insurance, creating a large pool over which flood risk costs are spread (ABI, 2011). The Statement of Principles was renewed in 2008 and was due to stand in place until June 2013 (Defra, 2008). Recent increases in claims (O'Neill and O'Neill, 2012), the market distortion that favours new insurers and the forthcoming Solvency II Directive from the European Commission (2009b) requiring large (re)insurance companies to calculate their risks up to a 200 year return period mean that the Statement of Principles was considered unsustainable (Crichton, 2012).

June 2013 did indeed see the replacement to the Statement of Principles announced in the much anticipated form of a national Flood Reinsurance Scheme (Flood Re). Under this scheme the government oversees the creation of a not-for-profit flood fund (Flood Re) that is used to ensure affordable flood insurance is available to all householders in houses built after 2009 (ABI, 2014b). Insurance providers have the amount they are allowed to charge for the flood aspect of a household insurance premium capped to a reasonable amount. If the insurer feels unable to provide flood insurance for the capped premium amount (on the basis of their own modelling of flood risk), they can cede the insurance to the Flood Re pool (Defra, 2013a). The pool is funded by the capped premiums (paid by the householder via the insurance company) along with an additional cross subsidy from all other household insurance premiums (ABI, 2014a), with the government primarily responsible for 'catastrophic' losses that Flood Re could not meet (Bennet and Edmonds, 2013). Importantly, the scheme is based on a cap that insurers can charge householders, not on a quantified level of flood risk, as was the case for the predecessor, the "statement of principles". The European Commission approved the Flood Re scheme under state aid rules on 29 January, 2015 (European Commission, 2015).

### 9.2.3 Land use regulation and planning

The planning process may be the most effective way of implementing the new policies by influencing the location and resilience of developments with respect to flooding (White and Richards, 2007). For over 60 years flood risk management policies have been examined in the context of flood risk being the product of the probability of inundation and the consequences (White, 1942), this can be summarised as  $risk = probability \times consequences$ . White points out that the erection of a flood defence scheme to provide a protected area on a floodplain will tend to result in an increase in development and population in the protected area of the floodplain. So although the erection of the defence reduces *probability* of inundation, the subsequent development increases the *consequences* of inundation to the extent that the overall flood *risk* may increase, this is referred to by White (1942) as the 'levée effect'.

This situation is clearly not the intention of policy makers in the UK who are moving away from the post-war policy of attempting to remove flood risk through the extensive construction of hard defences towards a strategy of *Making Space for Water* (Defra, 2004b). The risk-driven approach and the growing importance of flood damage assessments emphasises the need for flood risk mapping to promote adaptation and raise awareness of those most at risk (Porter, 2010). Under the Flood Directive of the European Union, enacted in November 2007, member states are required to produce flood hazard and flood risk maps for 3 probabilistically defined scenarios: "(a) floods with a low probability, or extreme event scenarios; (b) floods with a medium probability (likely return period  $\geq 100$  years); (c) floods with a high probability, where appropriate." (European Commission, 2007).

In the UK the Environment Agency has developed an Extreme Flood Outline (EFO) map to show all areas considered to be at medium or high risk of river or coastal flooding (Environment Agency, 2011d). In addition the maps give the location of recently constructed flood defences, and areas protected by those defences. What is lacking directly on the Environment Agency maps, and indeed most of the flood risk maps across Europe, is an indication of the uncertainty associated with the outlines given (van Alphen et al., 2009).

The Environment Agency has long been arguing for increased powers to prevent development in flood risk areas. Planning Policy Guidance 25 (PPG25), issued in 2001 (DETR, 2001a), required local planning authorities (LPAs) to consult with the Environment Agency and produce a Flood Risk Assessment (FRA) for all planning decisions in areas of high risk. In 1996 PPG25 was replaced by the stronger Planning Policy Statement 25 (PPS25), which gives the Environment Agency additional powers to order government reviews of planning decisions taken against its advice (DCLG, 2006). But even with this stronger regulation, the percentage of new homes being built in areas of high flood risk was higher in 2008-10 (9-11%) than in the late 1980s (7-8%) (Porter and Demeritt, 2012).

PPS25 dictates that flood risk assessments (FRAs) must be prepared for proposed developments. The FRA provides the information required for a 'sequential approach' designed to steer development towards the areas of lowest likelihood of flooding. Specifically, the sequential approach means preference should be given to locating the new development in Flood Zone 1 over sites in Flood Zone 2 and only allow development in Flood Zone 3 if an 'Exception Test' is applied (Communities and Local Government, 2010). Flood Zones 1, 2 & 3 are defined by the Environment Agency Flood Map for Planning (Environment Agency, 2011a), they are defined as follows (Environment Agency, 2014):

- Flood Zone 1. All areas where the annual probability of flooding from rivers or the sea is less than 0.001.
- Flood Zone 2. Areas where the annual probability of flooding from rivers or the sea is greater than 0.001 but less than 0.01 for rivers (or 0.005 for the sea).
- Flood Zone 3. Areas where the annual probability of flooding from rivers is greater than 0.01 and from the sea is 0.005.

#### 9.2.4 The allocation process of for FCERM

The UK has long prioritised its investments based on benefit-cost analysis and there is now very detailed appraisal guidance for the analysis with risk and uncertainty taken into account (see Environment Agency, 2010a). Section 8.9 briefly reviewed some of the damage models in different countries including the Multi-Coloured Manual (Penning-Rowsell et al., 2013) recommended as best practice in the UK by the Department for the Environment, Food and Rural Affairs (Defra) as a way of estimating the potential economic losses of floods (Johnson et al., 2007). But there is now a recognition in the UK that the appraisal of flood risk must go beyond a narrow economic cost-benefit analysis to encompass environmental and social concerns such that it is consistent with the UK government's principles of sustainable development (Johnson et al., 2007). These policies are made explicit in a Defra strategy titled *'Making Space for Water'* (Defra, 2004b), and funding for subsequent projects is allocated according to a scoring system that takes account of people and environmental issues. Under this scoring system, a proposed flood alleviation scheme can earn up to 20 points for economics (benefit-cost analysis) and 12 points each for social and environmental factors (Johnson et al., 2007), but this simplistic approach hides the difficulty of quantifying social and environmental costs and avoids the endemic subjectivity therein.

Project appraisal reports must be completed before for flood defence schemes can be built. A significant part of the appraisal process is to estimate the benefits the proposed schemes will bring by reducing the probability of flooding. This topic and the role of loss-probability curves were discussed in the context of flood risk in Carlisle in the previous chapter. The Environment Agency aims to focus on schemes with a high benefit to cost ratio and expects to achieve an average of 8:1 for projects in the current spending review period to 2015 (National Audit Office, 2014).

The 'Flood and Coastal Erosion Risk Management appraisal guidance' (FCERM-AG) document published by the Environment Agency (2010a) provides the best practice implementation guidance and supports the government policy as laid out by the preceding Defra policy statement (Defra, 2009). In particular the Defra statement sets



out the following principles that should be adhered to when considering flood management activities:

“Give more consideration to ‘risk management’ and ‘adaptation’, as opposed to only ‘protection’ and ‘defence’;

Are undertaken consistently, transparently, with value for money in mind and in a way that complies with the Treasury guidance on appraisal and evaluation in central Government (The Green Book) (HM Treasury, 2011);

Help achieve better social and environmental outcomes as part of sustainable development, both by considering a broader range of issues and by using a broader range of analysis techniques;

Adopt a risk-based approach, whilst considering impacts within the whole of a catchment or shoreline process area.” (Defra, 2009)

Within ‘the Green Book’ from HM Treasury there is an emphasis on assessing how “future uncertainties can affect the choice between options” (HM Treasury, 2011). The Green Book goes on to recommend sensitivity analysis and Monte Carlo analysis techniques as ways of assessing the consequences of uncertainty (HM Treasury, 2011). These recommendations are translated in the FCERM-AG as a need for proportionality:

“The guidance recognises that proportionality is needed in the effort expended on addressing uncertainty within appraisals.” (Environment Agency, 2010a)

This can be expressed as a judgement as to whether enough information has been collected to make a robust decision (Environment Agency, 2010a). Examples are given of where and when to focus effort in data collection or consultation but it is left to the discretion of the practitioner to decide the extent of uncertainty analysis required.

In spite of the provision of substantial appraisal guidelines, it seems the allocation of resources is not immune to political interference. The flooding of the Somerset Levels by the Rivers Parrett and Tone in late 2013 and early 2014 left 17,000 acres of farmland under water (The Guardian, 2014b). The flooding garnered a

disproportionate level of media attention in spite of the relatively small number of properties inundated (NCE, 2014). A successful lobbying campaign by the local farming community sparked several visits by politicians and criticism of the Environment Agency for not dredging the rivers (BBC News, 2014b). In February 2014 the Agency agreed to direct £4.1m towards dredging the Rivers Parrett and Tone (BBC News, 2014a), even though the benefits were at best debatable (CIWEM, 2014). It seems this benefit-cost analysis guidance was not strictly adhered to in this case (BBC News, 2014a; NCE, 2014; The Guardian, 2014a).

#### 9.2.5 Communication of risk and uncertainty

As the policy in the UK shifts from one of attempting merely to constrain floodwaters based on an economic cost-benefit analysis to one encompassing broader environmental and social concerns (Defra, 2004b), so the importance of collaboration between experts at all levels, policy makers and the public increases. Research projects such as FOSTER (2010), PREVIEW (see Nobert et al., 2010) and D-PHASE (see Frick and Hegg, 2011) aim to improve communication between flood scientists and local decision makers in flood prone areas with the aim of promoting understanding and trust.

Risk perception and communication work have identified a number of factors that influence how risk information is understood and thus how it might best be communicated both between sets of 'experts' and to the public (Demeritt and Nobert, 2014; Kahneman, 2011; McComas, 2006). Covello (1986) breaks down the issues of risk communication into 4 components: message source; message design; delivery channel; and target audience. But it is clear that within these components there are many psychological factors brought to bear on an individual's response to risk. Personal experience of the hazard itself is known to greatly amplify the perception of the risk. Gross and Aday (2003) found that fear of crime is affected vastly more by personal experience of the crime than local television reports. This would also seem to be the case for flooding where previous victims of floods are more likely to implement defences (Harries, 2008; Viglione et al., 2014).

It is not entirely clear where the public's perception of the risk of flooding lies. This is partly due to the huge variation in size and destructive power of flood events, but also due to the uncertainties, ambiguities and contradictions associated with them: Why is development still permitted in flood prone areas? Are floods becoming more frequent and damaging? Are floods a natural hazard or is land use change to blame (O'Connell et al., 2007)? Do flood defences in one area worsen upstream or downstream flooding? How reliable are predictions of future flood events if they are based on evidence from the past (Lane et al., 2011b)? Is anthropogenic climate change likely to cause an increase in flood frequency and intensity as suggest by the IPCC (2007)?

These questions aside, the specific point of how best to communicate the likelihood of inundation continues to be a vexing issue. Studies have shown how the framing of the uncertainty is vital for public understanding (Patt and Dessai, 2005) and furthermore, poorly framed communication of uncertainty not only leads to miscomprehension, but also mistrust in the model and modelling process (Pappenberger and Beven, 2006). Often within the flood research community, the severity of a flood is referred to by the return period of the event, such that 100-year flood is one that has a 1% chance of in any year, and 1000-year flood has a 0.1% chance. This terminology spread beyond experts and administrators and the use of the phrase '100-year flood' was adopted by policy makers and in risk communication channels as an efficient shorthand (Bell and Tobin, 2007). The scope for misinterpreting the meaning of the phrase and the possibility of its oversimplifying the uncertainty has led some to question the validity of its use (Smith, 2000). Bell and Tobin (2007) commissioned a questionnaire of residents in a flood prone area in the US with 4 descriptive methods:

- 100 year flood
- 1% chance of a flood per year
- 26% chance in 30 years
- Flood risk map.

Respondents were asked to rate the 4 methods of communication in terms of ease of understanding, persuasiveness (likely to change the behaviour of the recipient) and perceived accuracy. Whilst '100-year flood' was deemed the most persuasive form of communication it scored lowest in terms of understanding. These ratings were reversed for the phrase "1% chance of a flood per year". The method of communication with the highest perceived accuracy was the flood risk map with the possible by-product of incorrectly dividing areas as either 'flood-prone' or 'flood-free' in the mind of the recipient (Bell and Tobin, 2007).

Providing the recipient with a single figure defining the likelihood of inundation masks the recipient not just of features of floods such as water depth and velocity that are hugely important in the damage inflicted (Tunstall et al., 2007), but also the many inherent sources of uncertainty present when calculating the extent of a '100-year flood' (section 2.9.13). If these sources of uncertainty in flood prediction are hidden from the recipient it is perhaps unsurprising that uncertainty may be viewed as an 'information deficit' that can be rectified rather than an unavoidable feature of environmental research (Brown, 2010).

Falkner et al. (2007) suggest the need for a translational discourse between scientists and practitioners that would improve communication of uncertainty through the use of agreed semiotics. This would help bridge the motivation gap whereby scientists are interested in establishing and communicating 'scientific uncertainty' perhaps in the form of a probability distribution, but the decision maker is only interested in the effect this may have on their decision making processes ('decision uncertainty'). So, for example, if there is covariance in loss probability curves such that the residual damage uncertainty is greatly reduced, this means the scientific uncertainty of the flood risk will not really have much impact on the decision to build a flood defence. Furthermore, Faulkner et al. (2007) point out that "scientists do not necessarily agree about how to do an uncertainty analysis" and this is borne out by the number of different methods published in academic journals, none of which seem to take account of every single source of uncertainty. So if there are multiple ways of estimating uncertainty that means multiple possible translations if the meaning of uncertainty. One approach to address this issue is to develop guidelines for good

practice (Beven et al., 2014) in the hope that they are adopted as an ‘industry standard’ (for example Beven et al., 2011; Beven and Alcock, 2012; Hall and Solomatine, 2008).

### 9.3 Data and methods

As well as reviewing the body of literature covering these questions, the research has taken the form of semi-structured interviews with 24 respondents, either one-to-one or in small groups. The interviewees included representatives from the Environment Agency, the Department of Environment, Food and Rural Affairs (Defra), insurance and reinsurance companies, flood and catastrophe risk modelling companies, local authorities and victims of flooding. Beyond the interviews and officially published literature sources, on-line discussion forums (for example the British Hydrological Society group on LinkedIn, 2014) have been surprisingly productive sources of relevant comments and anecdotes.

The breadth of issues influencing flood risk uncertainty and the wide range of stakeholders interviewed meant that it was not feasible to structure the interviews such that the same questions were addressed by all stakeholders to the same technical level. Indeed a feature of the research carried out for this chapter is the question ‘how much context is enough?’ The ‘governance’ referred to in the chapter title can be broken into three separate, but interrelated, areas: insurance, planning and management of flood defence assets (as listed above). But within each of those areas a number of actors spanning many different types of commercial organisation were included, and not forgetting the public living in areas of possible flood risk. It was deemed inappropriate to attempt to form a picture of the implications of flood risk uncertainty through techniques such as polling or questionnaires of representative samples of each stakeholder group. The subject matter is too technical and the levels of knowledge between types of stakeholders too broad for any sort of tick-box style interrogation. Rather, a series of more in depth, semi-structured interviews was arranged with a small number of correspondents.

Recruitment of interview subjects was carried out through many channels: the use of personal and academic contacts; meetings at conferences; social media (LinkedIn,

Facebook etc.); and emailing contacts identified from company websites. Anyone showing an interest in taking part in an interview was given an information sheet with consent form (see appendix A) that had been given approval by the King's College London's Research Ethics Committee. By signing the consent form, interviewees were giving informed consent for their quotes and opinions to be used in the research on the basis that all data will be anonymous and stored in accordance with the Data Protection Act 1988. The audio of all interviews was recorded allowing verbatim transcripts to be created with some level of non-verbal signalling included (see Cloke et al., 2004 p.159).

The interviews were conducted in two tranches. An initial set of interviews was conducted in the autumn and winter of 2012-13, with a second set conducted between May and October 2014 after a lengthy interruption due to illness. This break in the fieldwork means that interview data was collected from before and after the announcement of the national Flood Reinsurance Scheme (Flood Re) (Defra, 2013a), in June 2013 allowing consideration of what, if any, difference that made to the views expressed about uncertainty. Interviews took place at a location chosen by the subject (typically a communal space or meeting room at their place of work). In total 24 people were interviewed, mostly one-to-one, face-to-face meetings lasting, on average 45 minutes to one hour. Three interviews were performed over the 'phone. One meeting with a flood modelling company was attended by four of the company's representatives and two other meetings had two interviewees attending. The interview subjects are summarised in table 9.1

### 9.3.1 Interview structure

The face to face interviews were conducted with the use of a presentation on a laptop or tablet computer, the audio was recorded on a separate device. The first part of the interview consisted of the researcher summarising the research project and introducing the Carlisle 2005 flood case study using approximately 12 slides. This allowed the researcher to give the interviewee context on the problem and highlight some of the many sources of uncertainty in estimating flood risk. This part of the interview was timed to take approximately 20 minutes, but the interviewees were encouraged to ask questions and embark on discussion topics at any point.

Consequently, the presentation phase frequently lasted over 45 minutes. After the presentation, the following specific discussion points were listed and the researcher ensured that all points were covered in the interview:

- Uncertainty is unavoidable but deterministic maps of flood return periods used by many stakeholders in UK
- Distinction between risk and uncertainty
- How best to communicate uncertainty on flood risk maps?
- Problems introduced by including uncertainty on flood risk maps?
- To what extents do the flood models employed by (re)insurance companies take account of the uncertainty inherent in assessing flood risk?<sup>5</sup>
- How might the replacement to the Statement of Principles policy incorporate measures to handle uncertainty to avoid distortion of insurance premiums for the households located on the edges of zones defined as high flood risk?<sup>5</sup>
- How might flood maps such as the Environment Agency's EFO or those incorporated in FRAs communicate uncertainty when defining flood zones?
- What might be the effect on the planning application process for the cases where applications lie in areas of uncertainty between flood zones? Resilience?<sup>6</sup>
- How might cost benefit analysis of flood mitigation schemes be affected by uncertainty?
- Anything else?

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<sup>5</sup> Specific to subjects involved in insurance.

<sup>6</sup> Specific to those involved in planning decisions.

Table 9.1 Summary of interview subjects

Category	Organisation	Role(s) of interviewees	Date
<b>Insurance</b>	Insurance company	Chief Insurance Risk Actuary	13/11/2012
	Association of British Insurers (ABI)	Policy Advisor, Flooding	11/12/2012
	(Re)insurance company	Chief Scientific Officer	17/12/2012
	(Re)insurance company	Property Catastrophe Underwriter	2/5/2013
<b>Flood modelling</b>	Engineering company	Associate Technical Director, Flood Risk and Water Management	30/10/2012
	Flood modelling company	Managing director, technical director, flood risk consultant, technical manager	4/12/2012
	Engineering consultancy	Water group manager, flood management scientist	19/12/2012
	Risk management company	European Flood product manager	8/1/2013
	Dr Dave Leedal	Research associate, Lancaster University	2/6/2014
	Risk management company	Senior director, flood modelling	25/6/2014
<b>Government</b>	City Council	Senior Engineer	11/11/2012
	City Council	Flood Mitigation Manager	21/12/2012
	Defra	Head of Research, WFRM Analysis & Evidence Team	11/6/2014
	Defra	Team Leader – Local Flood Risk Management and Resilience, Mapping and modelling lead	2/10/2014
<b>NGO</b>	Environment Agency	Flood risk manager	22/5/2014
	Environment Agency	Flood risk management advisor	23/5/2014
	Environment Agency	Deputy Director FCERM	3/7/2014
	Environment Agency	Flood Risk Senior Advisor	1/7/2014
<b>Public</b>		Homeowner with experience of flooding	11/6/2014



## 9.4 Findings

### 9.4.1 Issues facing the insurance industry (current situation)

The evolution of flood insurance policy in the UK seems to follow a progression that is dictated by the ability to use technology to quantify flood risk. Since 2003 when the “Statement of Principles” was introduced, flood insurance policy has been predicated on the ability to place a figure on the probability of a property being flooded in any one year (even if the 1 in 75 annual probability referred to in the statement of principles was in fact the result of a compromise between the insurance industry who wanted 1 in 100 and the government at the time who wanted 1 in 50 (interview, ABI Policy Advisor)). This naturally begs the question, how is the flood risk of a property calculated? In the USA inherent uncertainty in these estimates of flood risk is often seen as inadequately addressed during discussions of flood insurance (Huber, 2012), but the impact of a property falling just within an area defined as high flood risk may have a significant financial impact on the homeowner in terms of insurance premiums and property value (Zia and Glantz, 2012).

Staying in the USA for now, an objective measure of the difficulty in defining risk zones is shown by the results of a study detailed by Tobin and Cafree (2005). During a review in 9,500 mortgage loans in the US in 2002, four flood determination companies were asked whether the associated properties were within the 100 year return period flood zone. There was disagreement amongst the flood determination companies for over two thirds of the properties (Tobin and Calfee, 2005). This gives some indication of the extent of uncertainty in the Federal Emergency Management Agency (FEMA) flood risk maps underlying these estimates. Awareness of this uncertainty and the provision by FEMA of a facility whereby property owners can request to have their flood hazard designation changed (FEMA, 2015), is opening the system to controversy (see for example NBC News, 2014).

In the UK again, the investment within the insurance industry into flood risk mapping is difficult to quantify due to commercial confidentiality. It is in the interests of the insurance companies to identify the level of flood risk for individual properties as long as the cost of doing so makes it worthwhile, but in 2010 it was estimated that

only one fifth of householders in areas of increased flood risk were paying a premium to reflect this increased risk (Defra, 2013b). To this end, insurance companies have been working with engineering consultancies to generate their own national flood risk maps. For example Aviva plc (previously Norwich Union) in conjunction with JBA Consulting started work on a property level map of flood risk in 2003 (Aviva, 2004), subsequently enhanced to include the risk of surface water flooding (Aviva, 2010). It is believed that the majority (75 %) of Insurers now use JBA's maps (Interview, Team Leader Defra).

The Flood Re reinsurance scheme due to be implemented in the summer of 2015 (Bennet and Edmonds, 2013) will continue to provide a mechanism for subsidised insurance even for those at very high risk, although frequently flooded properties that don't implement resilience measures may be excluded from the scheme in time (Water Bill Committee Debate, 2013). It is envisaged that Flood Re will be required for an estimated 25 years while the insurance industry makes a full transition to risk reflective pricing (Flood Re, 2014).

Although there is no suggestion that the insurance industry ignores the uncertainties in the methods and data used for flood risk assessment, it doesn't necessarily follow that quantifying or reducing these uncertainties is a priority. The issue, first discussed in chapter 8 and revisited here, is that uncertainty becomes priority only when it affects the outcome of decisions. In the case of the insurance industry one of the specific decisions to be made is whether or not to underwrite the risk, and what premium to charge.

"I think what insurers rely on in their underwriting functions particularly is simple, and this is increasingly the case, simple databases which can be fully automated and fully brought into actually pretty simple rating algorithms and rating functions, and at the moment I don't think that exists for uncertainty and flood risk." (Interview, ABI Policy Advisor)

This quote emphasises the extent to which insurers rely on automated systems and algorithms in their decision making processes that don't necessarily sit well with the concept of uncertainty. This attraction to automated systems may well be driven by

the insurance company to reduce costs, but is also perhaps desired by the consumer, most of whom value convenience:

“What I want as a policy holder is to have convenience on line and, as long as I’ve got enough cover, making sure I get the right rate. Click, click, click and I’m done. And most people in the country want that type of thing.” (interview, Chief Scientific Officer, (re)insurance company)

Suggesting that it may be possible to send out an expert underwriter who could generate a more precise estimate that took uncertainty into account, but for simple domestic buildings insurance, the benefits in terms of a more precise estimate of risk, do not outweigh the costs of generating that estimate.

Furthermore, the tendency for insurers to rely on a small number of flood modelling providers leads to uniformity within the industry:

“I think the problem is as well, of course, everyone in the insurance industry at the moment uses the same models... so we are inclined to get quite similar answers and so therefore we’re all going to charge the same sort of prices and we might make the same underwriting decisions so there’s a bit of practical groupthink.” (interview, Chief Insurance Risk Actuary, (re)insurance company)

One example of a situation that may highlight errors or uncertainty in the underlying risk maps is the advent of claims in an area not deemed at risk:

“for example, where the JBA data or EA data or whatever they’re using says ‘that housing estate is not a flood risk’ and they’ve got claims in it or vice versa that’s the kind of occasion when they’ll look at it and start to think ‘what’s going on here?’ There must be an uncertainty factor there, that kind of thing, and that’s kind of a manual informal process at the moment” (interview, ABI Policy Advisor)

Similarly, in areas where flooding flood risk may have been correctly estimated, the extent of losses as a consequence of a flood event can highlight important

uncertainties in flood damage modelling. Referring to the 2011 floods in Thailand (Thai Water, 2012):

“The Thailand floods are a good example where everyone knew it floods in Thailand. What was surprising was the amount of business that is focussed in those areas, that’s what the unexpected element was” (interview, Chief Scientific Officer, (re)insurance company)

### **A question of priorities?**

If uncertainty only becomes an issue when unexpected losses occur that suggests insurance industry priorities lie elsewhere. Certainly, it seems the priority for the insurance industry is to adopt more detailed deterministic flood maps including all sources of flooding rather than finding ways to quantify uncertainty and account for it in insurance premiums; as Policy Advisor from the ABI states:

“that’s where I get the most comments and worry from insurers at the moment; it doesn’t tend to be about uncertainty within risk models. It’s about there aren’t any risk models for flooding from surface water and therefore they’ve got 100% uncertainty” (interview, ABI Policy Advisor)

This issue of priorities is perhaps even better emphasised by Chief Insurance Risk Actuary for a large insurance company who made the point that some companies only assess flood risk at postcode scale, rather than by individual property.

“Some companies for example don’t do location based rating, basically you pay for a unit so if a postcode unit is classed as bad those companies will just decline the whole group” (interview, Chief Insurance Risk Actuary, (re)insurance company)

Given that commercial strategy, there is simply no appetite for more detailed information about uncertainty with which to price the risk more precisely. The decision is simply a binary one: do we underwrite for this postcode or not? Flood Re is designed in part to address this issue and it is envisaged that over the next few decades location based pricing will more accurately reflect the risk to individual properties (Flood Re, 2014).

A Property Catastrophe Underwriter (interview) for a global reinsurance company makes the point that a large amount of new insurance business is in rapidly developing countries like China:

“One of the biggest things for us is areas like China where they are building at such speed in areas which would have been agricultural land 5 years ago there is no record of there ever being any rain apart from maybe local knowledge of a farmer may have known when his land was flooded so you’re really in the dark.”(interview, Property Catastrophe Underwriter, (re) insurance company)

Rapid urbanisation means developments are happening in data sparse areas, so pricing is based on data that is far more uncertain than that used for the UK. Across the portfolio as a whole, dealing with the comparatively small uncertainties in their pricing of their UK policies is a much lower priority.

However, if it isn’t a priority for insurers to meaningfully reflect uncertainty in the premiums they charge to customers, bigger decisions may require more careful consideration of uncertainty. The limits companies set on the aggregated risk in certain areas are more likely to be subject to formal uncertainty analysis:

“Where we need to look at that is not so much in the pricing because there’s very little we can do about that because it has to be a point. It’s how we aggregate our risk so if you think that the risk in a certain city is going to be X amount and the most we’re willing to have exposed at any one time is 40 million for a one in a hundred year event or 20 million for a 1 in 10 year event, 100 for a 1 in 1000 year event, then that is where we can bring uncertainty in: to know how much next year we want to have as a maximum probable loss in that area... so that’s where the uncertainty is more important for us, it’s how much risk we’d take on in a certain area rather than in the pricing.” (interview, Chief Scientific Officer, (re)insurance company)

### **How would greater consideration of uncertainty affect the insurance market?**

If there were to be a greater awareness of flood risk uncertainty within the industry, what might the effect be on the market? Several respondents highlighted the possible

loss of business and profits faced by individual insurers if they were to be amongst the first to start taking greater account of uncertainty in their retail pricing. This could either be because the uncertainty would make it impossible to price the risk:

“let’s say you had an area with a lot of uncertainty in it and it was reasonably high risk, I think insurers would walk away, I don’t think they’d want to write insurance there because they just don’t know how to capitalise it, how much do you want to reserve for that? No idea.” (interview, ABI Policy Advisor)

Or because quantification of the uncertainty would actually lead to lower income overall:

“In terms of what we charge our premiums it’s a market out there unfortunately. If we get a better handle on this than anybody else and it means that we realise there is a much greater risk in a particular part of Carlisle (say) than others do, so we try to charge 20% more than the others do we aren’t going to get the business.... if we think it could be 20% less then we go with a product that we feel had got those margins to make sure it works for us and it works for our clients. So then on average you would have to have thought for our portfolio the more we learn will reduce in terms of income because we’ll lose where we have to put the prices up correctly but we win when we put the prices down, so on average they will drop.” (interview, Chief Scientific Officer, (re)insurance company)

Although the same interviewee could envisage the benefits of convincing reinsurers that the insurers are operating at a reduced risk:

“maybe they would charge us less so maybe we could have some gains from that point of view because we’ve shown them look we really aren’t such a risk” (interview, Chief Scientific Officer, (re)insurance company)

But by taking a longer term perspective and considering the market as a whole, some could see the benefits. Defra Team Leader (interview) asserted that a better appreciation of uncertainty, whilst it may reduce opportunities for the larger, established players in the market, would open up opportunities for niche companies:

“So I think that particularly for insurance a better understanding of uncertainty in maps would be quite valuable for the insurance brokers and for the more specialist market that the brokers serve.” (interview, Team Leader Defra)

Furthermore, when considering the impact of uncertainty in the context of the forthcoming Flood Re reinsurance scheme, the natural tendency for big insurers to act conservatively in the face of uncertainty may lead to improved profitability of the Flood Re pool:

“So the stuff with greater uncertainty insurers’ natural reaction will be either to hike the premium up because of the uncertainty or to reject it because of the uncertainty...In a Flood Re scenario I think it’s quite interesting because insurers’ natural response won’t be to decline people, if for whatever reason people are not very desirable, their natural reaction will be to put them in Flood Re. So what happens if you’ve got a load of properties which are in Flood Re not necessarily because they have really high risk but because they are in high uncertainty? Actually you are going to make that pool more profitable, more viable, because you’ve got a lot of properties that are probably, genuinely not that high risk in there and therefore, because they are all paying the same amount, the lower risk a property is, the more profitable the pool.” (interview, ABI Policy Advisor)

Consideration of scale of the insured property leads to distinct approaches to the management of uncertainty. For household insurance where the profit for individual properties is limited and the customer often values convenience over a reduction in premium, the analysis of uncertainty is undesirable for both parties:

“What I don’t want when I renew my house insurance is to have maybe three or four different insurance companies each sending their underwriters to my house to assess my house compared to next door’s house for example. What I want as a policy holder is to have convenience on line...” (interview, Chief Scientific Officer, (re)insurance company)

Conversely, when pricing larger concerns the premiums and potential profit or loss per customer are much larger. In these cases, uncertainty analysis can be a useful tool in the negotiation process:

“It does give us a negotiating position in a sense that we think the premium should be ten pounds, our model says it’s really ten pounds plus or minus three and our underwriter might feel that this particular client is going to be a tough one, should we go down to nine? We might have room for manoeuvre there, to some extent, from our models. So we can do that internally and our model would take that into account.” (interview, Chief Scientific Officer, (re)insurance company)

Overall it seems, whilst there is certainly an appreciation of the inherent uncertainty in flood risk in the insurance industry, in many areas it is not a priority to quantify or account for it. This reluctance can only partly be explained by the additional resources that would need to be dedicated to the subject if it were properly managed; several interviewees pointed out that accounting for uncertainty in their pricing algorithms would lead to a disruption in the market with probable loss of business and profit for the established players. Further insight in the insurance industry’s attitude to uncertainty might be gleaned from the discussions with the flood modelling companies who provide much of the data to the insurance sector (see section 9.4.4).

#### 9.4.2 Flood risk uncertainty for land use regulation and planning

When considering flood risk uncertainty in the context of land use regulation and planning the most relevant question is not the quantification of the uncertainty, but whether the uncertainty affects the (often binary) decision that faces the stakeholder. As explicitly stated by Faulkner et al. (2007), acknowledgement and communication of uncertainty might be considered in an extremely negative light if it opens up policymakers’ decisions to scrutiny and appeal. This suspicion was echoed by those involved in planning at a local level.

“What would concern you is if that site was in an area which was shown to be at risk but had low certainty about the confidence in the flood zones at that



location because then it leaves you wide open to challenge and developers and people working on behalf of developers or consultants could use that as a crow-bar to try and get the development to go ahead.” (interview, Flood Mitigation Manager, city council)

And there is evidence that local planning authorities do grant planning applications against the advice of the Environment Agency on the grounds of the uncertainty (Paz, 2012 p. 64) and that uncertainty can be used to ‘manipulate’ risk calculation to give acceptable risk figures (Butler, 2008). But this negative view is not necessarily representative at a national level. The purpose of flood risk assessment in the planning process is primarily advisory, and the Environment Agency advisors are happy to work with developers’ consultants if they choose to provide their own flood risk estimates. If they agree with the methods employed by the consultants, the EA may update their maps appropriately:

“developers... would employ a consultant who would say ‘no this development is not a flood risk or we can find ways of accounting for the flood risk’, they would then as the developer’s agents submit that information to the local authority the local authority would share it with us or we might liaise directly with the developer on their behalf and we would say, as a statutory consultee, ‘we agree with their reassessment’ or ‘we don’t agree with their assessment’. If we do agree we look to change our maps in line with it.” (interview, Deputy Director Environment Agency)

This stands in contrast to the situation in the USA where the FEMA designated flood risk categories dictate the level of contribution residents make to the nation flood insurance program. Here, significant savings can be made if the level of flood risk can be downgraded for a high value property (NBC News, 2014).

The point was also made that consideration of flood risk is only one of a planner’s many responsibilities. Uncertainty in fluvial flood risk is by no means a priority when maps of flooding from other sources are not as well developed and the maps used by planners are already confusing enough without attempting to represent uncertainty:

“you’ve got a map with flood zone 3B, so functional flood plain flood zone, 3A: hundred year, flood zone 3A plus climate change, 20% allowance for climate change, flood zone 2 plus all the development sites on the map and it is extremely difficult to create a map with all those that is easy to read with all those bits of information even with just the flood zones on without any element of uncertainty” (interview, Flood Mitigation Manager, Environment Agency)

This sentiment is echoed by Senior Engineer at a city council (interview) explaining how hard it is to represent uncertainty on maps:

“If you tried to add uncertainty to that it would be impossible basically... It’s only really possible to vary one thing on the map isn’t it? If you’re going to show uncertainty you can only really look at one return period. Or you can have a map with different return periods or you can have a map with different depths and again it’s got to have one return period and no uncertainty. If you try and vary two things you’re going to get in a horrible mess probably.” (interview, Senior Engineer, city council)

The approach taken by the Environment Agency regarding flood risk uncertainty in the maps they provide on-line is to prevent individual property-level assessment of flood risk by limiting the zoom capabilities of the on-line mapping tools (Clark and Priest, 2008). The maps shown in figure 9.1 are extracted at the maximum zoom, and this policy is explained by Flood Risk Senior Advisor at the Environment Agency (interview):

“We basically use the maps to show people as much as possible without showing the individual properties because that would imply that the information is relevant at the individual property level.” (interview, Flood Risk Senior Advisor, Environment Agency)

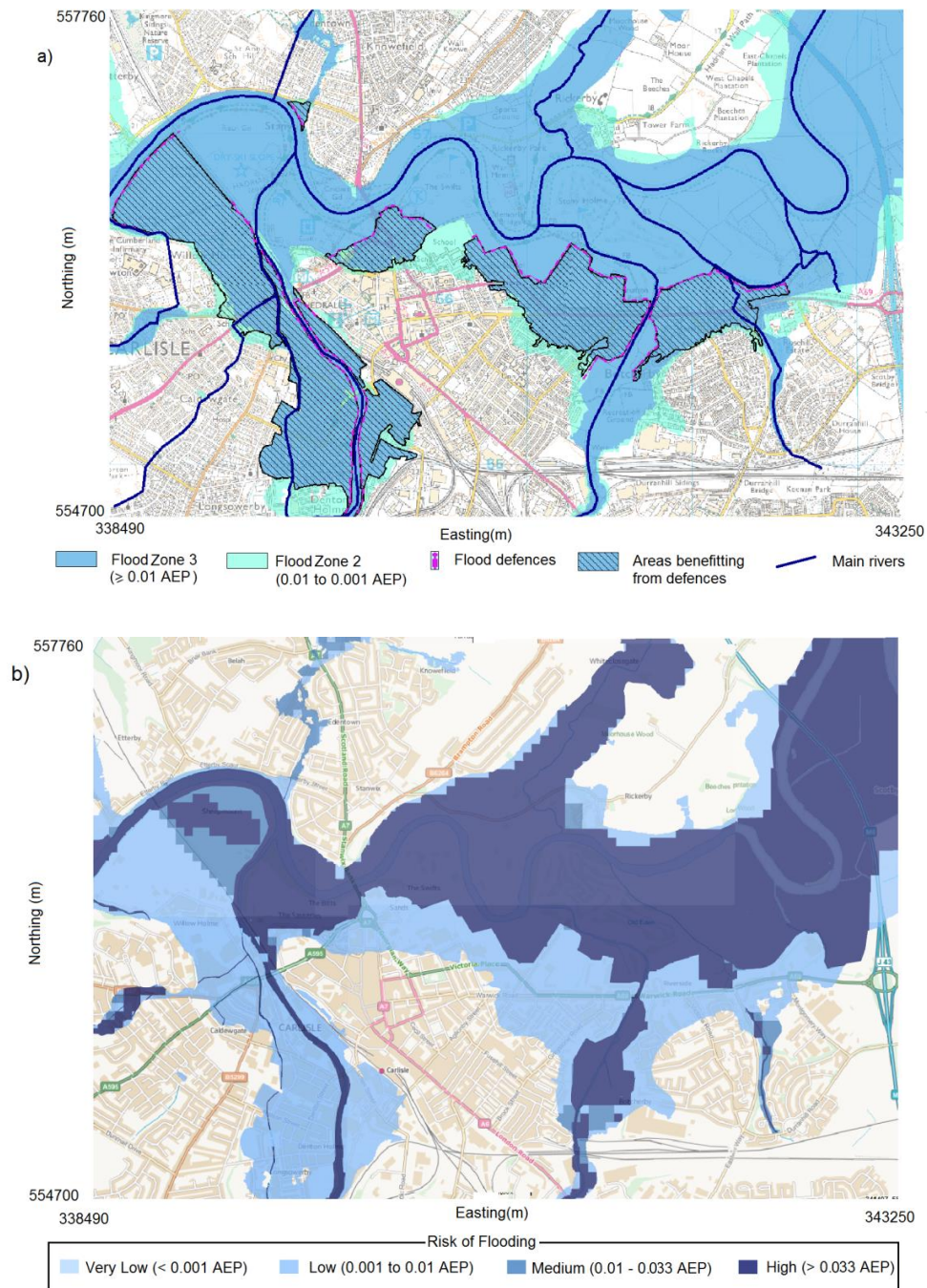


Figure 9.1. Publicly accessible flood maps for Carlisle, UK. a) "Flood Map for Planning (Rivers and Sea)", showing fluvial flood risk zones 2 (0.01 to 0.001 AEP) and 3 (AEP 0.01 or greater) (DETR, 2001b), zones do not take account of the presence of defences (Environment Agency, 2011d). b) "Risk of Flooding from Rivers and Sea", flood risk estimates from the Environment Agency's 2008 National Flood Risk Assessment (NaFRA) (Environment Agency, 2009c). Contains Environment Agency information © Environment Agency and database right. Background map © Ordnance Survey Crown copyright. All rights reserved. Environment Agency 10026380. Contains Royal Mail Data © Royal Mail copyright and database right 2014.

Underlying the on-line flood risk maps is the National Flood Risk Assessment (NAFRA) data which does include a 'confidence score' that gives some indication of the level of uncertainty in the flood risk estimates. The confidence score for any given pixel in the flood risk map can be inferred by clicking on a pixel and examining the page of text that is subsequently displayed. In areas of greater uncertainty the following form of words is found:

"You can use the information in this area to see **the approximate areas** that would flood, and which parts would be shallower or deeper." (Environment Agency, 2011b)

Elsewhere, where the confidence is higher and uncertainty lower, the text states:

"You can use the information in this area to see **the areas that would flood, which streets may be at risk of flooding**, and get an idea of the approximate depth of flooding." (Environment Agency, 2011b) (emphasis added by author)

#### **Towards an acceptance of uncertainty in planning**

This shows that the uncertainty underlying the flood risk maps is accessible, although no attempt has yet been made to represent it visually in the maps. It will be interesting to monitor the effect of the further dissemination of uncertainty in flood risk that happens as the Environment Agency opens up more of the NAFRA data to third parties. Flood Risk Senior Advisor at the Environment Agency (interview) voices concerns as to how the underlying NAFRA data on uncertainty may be used when the data is available for third parties to download and incorporate in their own maps:

"Because our data is all going to be open data soon, we're in a transitional process now, that will go away and people will be able to use the data as they like and other people will use our data and present it completely differently. So in one respect it's great because it will take away that zoom issue but on the other hand there is the worry that people will make inappropriate decisions using it, so it's how we can share the data more openly but in a way that helps people make good decisions." (interview, Flood Risk Senior Advisor, Environment Agency)

Several explicit methods for representing spatial uncertainty in 2-D flood risk maps have been proposed: Faulkner et al. (2007, figure 4) believe that clearer communication of uncertainty in indicative flood risk maps is inevitable and will become an important part of the planning decision process. They suggest making available a secondary map of uncertainty that sits behind the indicative flood risk maps. Wicks et al. (2008) propose representing the uncertainty on the same map using line-styles to indicate uncertainty. Both Christian et al. (2013, figure 7) and Leedal et al. (2010a, figure 2) suggest the use of colours to represent uncertainty – an approach that will work only when one level of flood risk is indicated by the map i.e. different colours cannot also be used to represent different levels of flood risk as in figure 8.1. Leedal et al. (2010a) go further by implementing interactive tools to allow the user to select the probability of exceedance for the 0.01 AEP flood. Whilst Leedal et al.'s on-line tool has been showcased to various professionals involved in flood risk at workshops and was generally received well (Leedal, 2014), it is not being developed as a standard way of presenting flood risk uncertainty to the lay public. Concerns were raised as to what would happen if the on-line tool was made available to the public:

“There was a little bit of feedback about how people would tend to try and anticipate problems that say the Environment Agency would have if the Environment Agency had a similar tool. So people would tend to zoom to their house and say ‘you’ve put me in a flood-zone’ especially if you go to one end of the uncertainty the inundation zone tends to get massive. People are now going to say ‘I’m now in a flood risk area and you are affecting the value of my house’” (interview, Leedal, 2014)

#### 9.4.3 Flood risk uncertainty for allocation process for FCERM investment

When discussing uncertainty in the assessment of flood defence schemes, there was a feeling that a suitably high benefit to cost ratio would obviate the need for much uncertainty analysis:

“Generally for the Environment Agency schemes to get funding from Defra, they need to have a cost benefit ratio of like 6 to 1, so you have to have 6 times as much benefit as you have costs, so you’re well above the threshold

really of what you reasonably would consider because the damages from flooding can be so huge.” (interview, Senior Engineer, Enfield Council)

Uncertainties in the cost of the scheme, for example hidden costs from land ownership issues could be dealt with by adding some padding to the cost estimates:

“the design that they’ve come up with that 2.4 million I think the scheme is going to cost something like one point something million but they’ve added quite a big percentage on for uncertainties in terms of ownership, compulsory purchase orders, risk and those kind of things.” (interview, Flood Mitigation Manager, Nottingham Council)

Elsewhere the benefits of using uncertainty analysis to test the robustness of decisions made where the choices between proposed schemes may be somewhat nuanced:

“if you’re deciding how long the wall is, how high it is, how much you’re trying to protect and to what sort of standard and the cost benefit will vary. If you build a bigger wall it will protect more properties but it will get more expensive, and there the uncertainty is very useful because, with the deterministic stuff you can look at the cost benefit as either your options change or within an option if you’re increasing the standard of protection... you can look at what is the best thing to do, but then if you use the uncertainty information it’s a really good way of testing if that decision is robust.” (interview, Flood Risk Senior Advisor, Environment Agency)

Suggesting how the analyst may expend more time on uncertainty analysis to help differentiate between competing schemes in a benefit-cost analysis if no preferred solution presents itself.

#### 9.4.4 Uncertainty in flood risk mapping

In many ways the flood modeller plays a central, but somewhat passive role in determining the acceptance and management of flood risk uncertainty. On the one hand the flood modeller has access to the knowledge, technology and data to define the most appropriate methods of handling and communicating uncertainty through their products, but on the other hand, as Faulkner et al. (2014) point out, they are largely restricted by the extent to which their clients wish to be exposed to uncertainty. There is no incentive for a flood modelling company to emphasise the uncertainty in their results beyond that which the client is expecting. The quote below from Associate Technical Director (2012) describes the “conundrum” facing those involved in modelling exercises when discussing uncertainty in sources of flooding:

“A reasonable amount of work that’s done in the background but then it doesn’t necessarily get taken forward to showing that, representing it and mapping it as an actual deliverable so that’s the sort of conundrum that we’re faced with: it’s not that we don’t understand the ways in which we could go forward in terms of using Monte Carlo simulations and the likes ... it’s not always requested of us and therefore we don’t provide what’s not requested of us.” (interview, Associate Technical Director, engineering company)

Explaining the difficulty of assessing the amount of uncertainty analysis to perform and present to a client if it has not specifically been requested. A seemingly popular resolution to the conundrum may be to provide their clients with the tools to infer the uncertainty in the modelling results by examining the sensitivity of the model response:

“As a commercial organisation we need to respond to commercial needs and commercial requirements and the way that they tend to deal with uncertainty is ‘well give me more return periods because then I can interpolate between them’ so, you know, improve the precision of the tool in a return period sense, because that’s one way of doing it is to look at the change if we go from 100 to 200 for example that’s a sensitivity analysis” (interview, Managing Director, flood modelling company)

“We tend to do things like give people sensitivity analysis tools which isn’t the same thing as a rigorous treatment of uncertainty with confidence bounds or anything like that” (interview, European Flood Product Manager, risk management company)

“Practically often we end up doing sensitivity and we’ll map the differences and the likely areas of sensitivity” (interview, Associate Technical Director, engineering company)

This then allows the assessment of the amount of ‘padding’ required to take account of the uncertainty in the modelling. In the case of insurers this padding may be added to the estimated annual loss of a layer passed to a reinsurance company:

“in the pricing of that layer is where the reinsurer might run our software, decide what the average annual loss is for that layer, they add that in their costs then they add in some padding.” (interview, European Flood Product Manager, risk management company)

But for planning purposes the ‘padding’ takes the form of a ‘freeboard’ added to the estimates of flood levels:

“in planning you try to remove uncertainty by simply putting an upper threshold in as with any engineering decision” (interview, Technical Manager, flood modelling company)

### **Exponential increase in complexity**

Those experienced in attempting to quantify the overall uncertainty point out how this can rapidly lead to exponential increases in model complexity and execution time as more sources of uncertainty are included:

“if you imagine pressing go on 40,000 simulations now add uncertainty where you want to perturb all of your inputs and understand the variance of all of your outputs and track it through your model process the whole thing goes exponential” (interview, Water Group Manager, engineering consultancy)



This point is backed up by figure 3 in Faulkner et al. (2007) which shows the expansion of uncertainties in a ‘ramped’ cascade where only the ‘control’ member of ensembles is taken to the next level in the ramp.

## 9.5 Discussion

The move towards an increasingly ‘risk based’ implementation across all three policy areas discussed in this chapter is necessarily dependant on probabilistic information of flood risk. Despite the endemic uncertainties in the probabilistic estimates, uncertainty is often not taken into account. Whereas in the past it could be claimed that is simply wasn’t possible, that is not the case now. The following discussion sheds light on what this might mean and examines similarities and differences in approaches to the management and communication of uncertainty across the various policy areas.

### **Awareness and acknowledgement of uncertainty in flood risk**

None of the interviewees dispute the existence of uncertainty in making flood risk estimates, and nobody disputed the rough estimates of uncertainty in flood frequencies and extent for Carlisle presented during the interviews. However the significance of this point may be overstated by the self-selection aspect of the interviewee recruitment process: it would be surprising if any of the individuals who agreed to take part in an interview about “uncertainty in flood risk” were then to deny its existence.

The literature reviewed and interviews performed certainly show an appreciation of the inherent uncertainty in flood risk across the stakeholder community. Whilst this does not imply that quantifying and representing uncertainty is necessarily the priority for professional stakeholders, the subject does seem to be well understood. As Policy Advisor from the ABI (2012) points out the challenge is the public’s appreciation of the problem:

“From the insurers’ side I don’t think there’s a problem at all. I mean there are practical issues putting it into underwriting systems but that’s not a problem it’s just a hurdle you’ve got jump over. I think the problem is the impact it

causes on the public who aren't experts at understanding risk and don't understand uncertainty is an important aspect." (interview, ABI Policy Advisor)

The emphasis of flood risk communication at the moment is on improving general awareness of risk of flooding from all sources rather than the subtleties of uncertainty versus risk. This can be seen on the website of the Flood Communications Public Dialog Project (FRCPDP, 2014) and is emphasised by comments from Flood Risk Senior Advisor at the Environment Agency (2014):

"It's like the fire service... you put a smoke alarm in your house, but you don't know the likelihood of your house burning; you don't know the likelihood of a fire in your house. So why can't it be like that for flooding? You don't need to know the likelihood of flooding to be able to take a reasonably appropriate action." (interview, Flood Risk Senior Advisor, Environment Agency)

However there is acknowledgement that perhaps the right balance has not been struck between conveying a simple message to the public and exposing more of the data in the science behind the advice:

"It's the balance between giving enough information to alert them to the fact they might be in an area of risk, you have to do that, but then 'how much risk?' is the next question. I don't have any answers but I worry that the professionals because you can do so much stuff ... have got to be more sort of streamlined. Try and strip away or condense some of that complexity put that behind the scenes and try and present as simple as picture as possible" (interview, Head of Research Defra)

It should be noted that this emergent theme that the public do not appreciate the subtleties in differentiating risk and uncertainty and should only be presented with a simplified picture is perhaps self-serving in that it authorises the organisations to afford uncertainty analysis a low priority.

**Not considered a priority**

Whilst there was across the board agreement that estimates of fluvial flood risk were inherently uncertain, it was generally considered as not featuring amongst the highest priority issues for the businesses that the interviewees worked for. The reasons for this lack of focus on uncertainty varied across the organisations. Several stakeholders stated that working on flood maps encompassing flooding from non-fluvial sources was more important than quantifying the uncertainty of just one source.

**Uncertainty as a possible threat**

This was a consistent theme, but generally for different reasons. Within the insurance industry the concern was that greater acknowledge of uncertainty would undermine existing businesses either by making it impossible to process certain risks or by opening up opportunities to new, specialist companies. For those involved in land use regulation and planning the threat was voiced that uncertainty would open up decisions to greater scrutiny and appeal.

For those involved in flood modelling and providing maps flood risk, including both private modelling companies and the Environment Agency, there was concern that attempting to quantify uncertainty would lead to an undermining of their methods by questions concerning the amount of uncertainty in the uncertainty figures themselves:

“At the moment there’s going to be so much uncertainty around the uncertainty itself, you kind of think ‘am I kidding myself for coming up with a statistical range of possibilities?’” (interview, Chief Scientific Officer, (re)insurance company)

This concern is perhaps part of the reason that the Environment Agency only alludes to the uncertainty in their flood risk maps using a comment half way down a page of text explaining the meaning of the flood risk estimates (see section 9.4.2).

## 9.6 Future directions

Overall the literature review and interviews showed a widespread acknowledgement of the uncertainty in fluvial flood risk estimates, but no consistent strategy of quantifying, managing and communicating that uncertainty (van Alphen et al., 2009). As Faulkner et al. (2007) point out, this may require the acceptance of a 'translational discourse' between scientists and professional groups which can then be extended to the general public using initiatives such as the current 'sciencewise' project (Sciencewise, 2014) which includes a series of public dialogues on flood risk communication. The prospect of using social media such as on-line discussion forums to improve communication, build up meta-data on flood modelling and harness local knowledge was highlighted by Dr Leedal (2014):

"People could start to build up knowledge about the process of how models get made who's making them...people could go 'I'm looking at this outline and it's showing that there's no water on whatever street, but during 2005 I know full well that it was under 3 feet of water' and then start to point out inconsistencies in the model ... so you can build up local knowledge and criticism and it can inform debate." (interview, Leedal, 2014)

However, Dr Leedal went on to point out how hard it is to raise the level of interest to the level required:

"it's very difficult to get that level of interest and get the ball rolling, so it's left open as a point of discussion for the rest of us to carry on with and say 'surely that is the way to do it: present your results present how the results were made as transparently as possible' and then provide a forum for asking questions for building up local knowledge, recording people's feelings" (interview, Leedal, 2014)

It seems that progress will be made along the following 3 strands:

- Scientists adopt a standard framework for defining the assumptions and managing uncertainty flood risk estimates as proposed by Beven et al. (2014)

- A structured 'translational discourse' is developed between scientists and other professionals involved in food risk management (Faulkner et al., 2007)
- Public communication on risk communication of environmental hazards

Furthermore, the rate of progress will partly be driven by the development of maps incorporating flood risk from non-fluvial sources (i.e. surface water, groundwater, drainage systems). It is likely that the emphasis will not shift to quantifying uncertainty in flood risk until policy-makers are satisfied that maps incorporate all possible sources of flooding.

## Chapter 10. Conclusion

### 10.1 Thesis aims and objectives

The stated aim of the thesis was to *present a method for quantifying the uncertainty in areas of flood risk and to explore the implications of uncertainty for flood risk management*. This was achieved by implementing a modelling chain for the Carlisle case study shown in figure 1.3 and completing the 5 more specific thesis objectives. The objectives are summarised here highlighting their importance in making an original contribution to the science of flood risk management.

1. *Estimate and minimise the uncertainty of observational data of the January 2005 flood in Carlisle.*

Chapter 4 examined the accuracy of the point observations of high water and flood extent. Lack of reference data hampered the quantification and identification of the inaccuracies in the data, but comparison of data point heights to nearby river gauge readings and neighbouring data points suggest an average uncertainty in the observational data of 0.105 m. *This method can be adopted as a standard and implemented simply with similar datasets to quantify observational uncertainty.*

A smoothing algorithm, designed to highlight the most inconsistent observations, was applied to the dataset to reduce the inconsistency between observations and their near neighbours. The efficacy of the smoothing algorithm was evaluated by comparing the 'raw' and 'corrected' measurements against the peak water level recorded by two river gauges in the study area, and the results suggested the correction algorithm was successful at reducing the error in the observational dataset. The algorithm was assessed through the use of a set of Monte Carlo simulations of a flood model of the event showing *how the smoothing algorithm can lead to improvements in model predictions by reducing model uncertainty*. Furthermore two clusters of point observations of flood extent were highlighted that showed distinct local inconsistency which would not be removed by applying the smoothing algorithm. *As well as*

*improving the overall accuracy of a set of point observations of flood extent, the algorithm provides the additional benefit of highlighting areas to the researcher about where it may be necessary to make further subjective inferences about the data.*

2. *Build a hydraulic model of the case study flood event and calibrate it against the uncertain observational data available.*

Chapter 5 gave a detailed description of running a Monte Carlo simulation of 999 model realisations of a LISFLOOD-FP model of the January 2005 flood in Carlisle. Using the GLUE methodology to calibrate the flood model allowed the creation of probabilistic flood maps visualising the spatial distribution of uncertainty in the extent of inundation due to uncertainties in the observational data, model parameters and structure.

In addition to calibrating the model using all data, equally weighted, it may be no less valid to apply a risk-based calibration scheme giving greater weight to observations in areas deemed more important to get right, because of the greater costs or other potential consequences of their being flooded. In chapter 5 a calibration scheme using only observational data points in urban areas was fully implemented using the same criteria as the global calibration. This resulted in little change in flood probabilities and no noticeable reduction in uncertainty. So it seems that for this case study, using the January 2005 Carlisle flood, when the uncertainty in the observational data is considered, the attempt to employ a more specific, risk-based calibration scheme gives no beneficial reduction in the uncertainty about the probability of flooding in areas where the costs and thus the overall risk are higher. This result is counter to that found by Pappenberger et al. (2007b) who, for their case study, state that “all the models considered acceptable in terms of global performance can be rejected on the basis of equivalent sub-domain performance measures. *Here it is demonstrated that the benefits of risk-based calibration are removed because the greater observational uncertainty in urban areas negates any*

*possible benefit of conditioning the model in a way that favours observations in the urban sub-domain.*

3. *Estimate the flood frequency curve for the study event with minimised uncertainty.*

Chapter 7 described the design and implementation of a Bayesian statistical model to produce a flood frequency curve with confidence limits that made use of uncertain historical flood data from Carlisle combined with systematic data from the Sheepmount gauging station. Figure 7.10 compares the flood frequency curves generated using the Bayes model with the single site analysis using pre-packaged WINFAP-FEH software from WHS (2009a) giving a graphical representation in the reduction in uncertainty across all return periods.

Chapter 7 also explained the incorporation of a subjective adjustment factor resulting from consultation with stakeholders with local hydrological knowledge. This may go some way to assuage the concern that flood frequency analysis is dominated by statistical analysis rather than hydrology (Singh and Strupczewski, 2002) with the caveat that it is important to communicate transparently how and why subjective factors such as those considered in chapter 7 are incorporated in the model and what the consequences of doing so are for model performance.

*The Bayesian statistical model developed in chapter 7 accounts for parameter uncertainty and errors in the gauged data and historical estimates, but still produces narrower confidence intervals for low frequency events than the packaged software recommended as best practice to Environment Agency flood risk managers. The statistical model was designed specifically to make optimal use of the relevant flood data available for Carlisle; however, data of that sort is not peculiar to Carlisle, so the Bayesian model could be adapted with minimal effort for use in other locations.*

It is conceivable that more widespread use of Bayesian statistical models for flood frequency could be encouraged if a generic model was available a commercial software package with improved user interface, documentation, error handling and support infrastructure. Although additional problems



specific to Bayesian Markov Chain Monte Carlo (MCMC) analysis would also need to be overcome, for example, the difficulty of identifying when the simulation is not converging on the posterior distribution (Lunn et al., 2013 p. 72).

4. *Run the design flood simulations using the results of the entire modelling chain and assess the consequences.*

In chapter 8 the outputs from the model chain components were combined into a Monte Carlo simulation of flood events to estimate the uncertain effects of design floods in Carlisle in terms of financial risk and risk to population and property. They were presented as probabilistic maps of the 0.01 AEP design flood in Carlisle. Whilst deterministic maps were not inconsistent with the Environment Agency's estimates of flood risk in this area (see figures 8.5 & 8.6), when the model uncertainty was included, the quantification of risk to property and population shows wide confidence intervals (section 8.8). The sensitivity of the model to various aspects of the modelling chain was interrogated, and the model was found to show most sensitivity to the peak discharge into the study area.

It was demonstrated how the results of the modelling chain might be used for benefit-cost analysis of flood protection schemes in Carlisle, but it seems there are still fundamental questions over what should be considered in terms of both the costs (Viavattene and Faulkner, 2012) and benefits (Defra, 2004a) of schemes. However, the uncertainty in the consequences of flood events, which has been discussed here but not quantified, is potentially greater than all other uncertainties put together. Yet modelling flood consequences and damage costs is often treated as an afterthought and has received comparatively little scientific attention compared to the enormous effort put into improving the hydrology and hydraulics (Merz et al., 2010).

5. *Assess the relevance of the results in the wider context of governance by investigating the importance of and methods employed in the management of uncertainty when assessing fluvial flood risk.*

Chapter 9 summarised the results of a series of semi-structured interviews with a range of stakeholders concerned with flood risk. The respondents were predominantly professionals and experts in their field, all providing insight into the acceptance and management on uncertainty in the organisations they represented. Whilst there was certainly no suggestion that flood risk is an exact science, the provision of quantified uncertainty bounds was generally not considered a priority.

Positioned at the end of a research project examining the physical science of flood risk science, chapter 9 perhaps provides *a unique insight into the status and priority of managing and communicating flood risk uncertainty in the policy areas of insurance, urban planning and the allocation of flood defence resources.*

## 10.2 Critical evaluation of methods

The model chain developed to provide the uncertain estimates of flood risk in Carlisle was never intended to take account of all sources of uncertainty. It is important when providing uncertainty estimates to be transparent about what sources of uncertainty have been quantified and to communicate clearly about which sources are not included. This allows the reader to make their own subjective judgement on the value of the data and the likely ‘uncertainty within the uncertainty estimates’. Section 8.10 in chapter 8 includes a summary of the main sources of uncertainty that haven’t been directly estimated in this project.

The various datasets described in chapter 3 were all provided by secondary sources. Whilst the modelling and statistical methods employed throughout the thesis were designed to accommodate errors in the input data, it is still the case that the reliability of secondary data cannot be guaranteed so larger errors may be present than were accounted for. In particular the estimates of historical floods made by Smith and Tobin (1979) are somewhat opaque, so perhaps a more conservative approach to their use in estimating the flood frequency curve for Carlisle would be preferable.

The Monte Carlo simulations described in chapter 8 involved running over 21,000 flood simulations of Carlisle. From these results, uncertain estimates of extreme floods between 0.05 and 0.001 AEP are made. Ideally, many more simulations would have been performed in order to capture better the tails of the confidence limits. Although the use of the Condor parallel computing environment (University of Bristol, 2014) eased the logistical difficulties of running many simulations, the quantity of output data meant the collation and processing of results was problematic because not all the steps were automated. Additional investment in ways to improve the logistics of running and processing the results of large Monte Carlo simulations would improve the results. This may only provide a small, incremental improvement, but it should come at minimal cost as it is dependant solely on greater exploitation of the ever increasing availability of computer resources.

Section 8.6 describes the limited sensitivity analysis performed to indicate the relative importance of the various sources of uncertainty. It may be considered worthwhile to redesign the modelling chain with the aim of allowing clearer, more definitive sensitivity analysis. Not only would this clarify the relative importance of the sources of uncertainty included in the modelling chain, but it would also allow investigation into the effect of adding additional sources of uncertainty listed in table 8.2 not currently included. Furthermore, it may be possible to elicit better indication of which links in the modelling chain would provide the most benefit from improvement. For example, the relative timing of the flood peaks on the three rivers in the study area and the approximation of flood peaks as triangular hydrographs is based on only 73 recent events recorded on the three rivers; this may be insufficient to correctly encapsulate the natural variability.

The 24 subjects interviewed for the social research in chapter 9 provided a wealth of insight into the importance of and methods for managing uncertainty in their organisations, and certainly provided enough material to fill the chapter. But it is acknowledged that the interview subjects only represent a small portion of all stakeholders to whom uncertainty in flood risk are relevant. Given greater resources and time it may have been possible to make contact with more respondents and

perform some quantitative analysis to provide a fuller, more structured summary of the status of flood risk uncertainty across the three policy areas.

### 10.3 Next steps

The research presented here suggests several opportunities for future research and also the direction uncertainty management may progress beyond academia.

The use of Bayesian techniques in statistical inference is emerging as an important technique beyond academia in many areas (e.g. epidemiology: Broemeling, 2013). It seems likely that the technological hurdles holding back its wider adoption in flood frequency analysis will be overcome sooner or later providing more robust flood frequency estimations with reliable confidence intervals. Currently flood frequency estimation is viewed somewhat as an art rather than a science, with the FEH methods only providing part of the solution. Indeed the FEH itself concedes that “different users will obtain different results, by bringing different data and experience to bear” (IH, 1999). The goal therefor should be to provide software that is flexible enough to accommodate the subjective choices required of the practitioners and allow them to reach their conclusions in a transparent, rigorous manner.

In chapter 8 the impact of the 0.01 AEP flood in Carlisle showed the most sensitivity to the peak discharge of the hydrograph on the River Eden. This suggests that improving the skill and reliability of flood frequency analysis should be a priority for the field of flood risk management. The improved flood frequency analysis methods should be incorporated in a generic framework for assessing flood risk uncertainty such as that proposed by Beven et al. (2011) that is flexible and extensible enough to make the best, subjective use of the locally available data and knowledge.

It should be feasible to use the proposed framework to adapt the guidelines for benefit-costs analysis such that they are not open to manipulation. Furthermore, Lane et al. (2011b) point out how the analysis is shaped by the risk management requirements and that the procedures employed in the analysis should be open to public interrogation. Similarly, by opening up the flood risk assessments of local planning projects to greater involvement of local, non-certified ‘experts’ as suggested

by Lane et al. (2011a), costly mistakes such as those that led to the flooding of the Glasdir estate in Ruthin, 2012 might be reduced or avoided.

The preceding point doesn't necessarily mean halting or even reducing development in flood prone areas. There is and will remain huge pressure to build more houses particularly in the South East of England where there is also reluctance to build in greenbelt or on greenfield sites. But brownfield sites may be in flood prone areas (which may be why they are brownfield). The emergence of new technologies (see for example Construction Manager, 2014) to add flood resilience to properties (rather than just 'raised finished floor levels') gives planning officers and developers more options when negotiating in the face of uncertain estimates of risk.

For the insurance industry, the move to a risk-based market for householders is currently nascent (Defra, 2013b), suggesting it may be some time before insurance firms differentiate themselves by their approach to uncertainty estimation in flood risk. It is quite understandable that the Environment Agency and insurers should prioritise the incorporation of flood risk from all sources over the quantification of uncertainty, but there is perhaps now an opportunity to standardise and extend uncertainty analysis techniques such that they can be incorporated by the organisations when it is deemed appropriate by policymakers.

Different approaches to flood risk uncertainty should manifest themselves through an open and diverse insurance market. It is hoped that the implementation of Flood Re will allow the insurance market to develop into just such a risk-based market that is open to specialist providers willing to exploit niche markets such as those in areas of high uncertainty. The wide uncertainties in the seemingly overlooked field of depth damage modelling mean there should be ample opportunities for insurance companies to invest resources in this area and differentiate themselves as the market becomes more risk based. This, in turn, should lead to insurers motivating homeowners financially to implement flood protective measures to which they might otherwise be reluctant (Harries, 2008).

Better preparedness by the public to flooding can also be encouraged through improved communication and public appreciation of uncertainty. The uncertainty

underlying the Environment Agency's flood maps should be promoted and explained more clearly. If this is done directly on the mapping interface it needs to be clear and unambiguous to users not necessarily attuned to the difference between risk and uncertainty and will need to be applicable to all types of flooding.

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## Appendix 1. Information Sheet and Consent Form

The following 2 pages are a sample Information Sheet/Consent Form given to and signed by all interviewees. This form was signed off by King's College Research Ethics Committee (Ref: REP(GGS)/11/12-3).

## INFORMATION SHEET FOR PARTICIPANTS

REC Reference Number: REP(GGS)/11/12-3



### YOU WILL BE GIVEN A COPY OF THIS INFORMATION SHEET

#### **Flood risk uncertainty and its impact on planning decisions and flood insurance.**

We would like to invite you to participate in this research project, which explores how the uncertainties in assessing the extent of floods certain magnitudes (for example floods that are expected to occur, on average, once every one hundred years) are perceived and managed. For the purposes of my research I have been using data from the extreme flood in Carlisle, January 2005, which is proving to be a very interesting test case. I am interested in discussing how uncertainties in flood risk zones are managed by those involved in flood mitigation and the assessment of planning applications in areas of medium or high flood risk.

If you are interested in taking part in this research I would be keen to arrange an interview, preferably in person, so I can present the preliminary results of my research that will lead into a discussion of the handling of uncertainty in flood risk.

If you consent, the interviews will be recorded to facilitate analysis and the resulting data will be anonymized, and securely stored in accordance with the Data Protection Act 1998. No sensitive personal data will be recorded and data will only be used in the final report in an anonymized form.

Please take time to consider your participation and to discuss it with others if you wish. You should only participate if you want to; choosing not to take part will not disadvantage you in any way. It is up to you to decide whether to take part or not. If you decide to take part you are still free to withdraw at any time and without giving a reason. Do not hesitate to ask us if you have any questions or would like more information. Our contact details are below:

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## CONSENT FORM FOR PARTICIPANTS IN RESEARCH STUDIES

Please complete this form after you have read the Information Sheet and/or listened to an explanation about the research.



Title of Study: Flood risk uncertainty and its impact on planning decision and flood insurance

King's College Research Ethics Committee Ref: REP(GGS)/11/12-3

Thank you for considering taking part in this research. The person organising the research must explain the project to you before you agree to take part. If you have any questions arising from the Information Sheet or explanation already given to you, please ask the researcher before you decide whether to join in. You will be given a copy of this Consent Form to keep and refer to at any time.

- |   | Please<br>tick <input type="checkbox"/> or <input type="checkbox"/> |
|---|---|
| <ul style="list-style-type: none"> <li>I understand that if I decide at any time during the research that I no longer wish to participate in this project, I can notify the researchers involved and withdraw from it immediately without giving any reason. Furthermore, I understand that I will be able to withdraw my data up to the point of publication.</li> </ul> | <input type="checkbox"/>  |
| <ul style="list-style-type: none"> <li>I consent to the processing of my personal information for the purposes explained to me. I understand that such information will be handled in accordance with the terms of the Data Protection Act 1998.</li> </ul>   | <input type="checkbox"/>  |
| <ul style="list-style-type: none"> <li>I consent to my interview being recorded.</li> </ul>   | <input type="checkbox"/>  |

Participant's Statement:

I \_\_\_\_\_

agree that the research project named above has been explained to me to my satisfaction and I agree to take part in the study. I have read both the notes written above and the Information Sheet about the project, and understand what the research study involves.

Signed

Date

### DELETE IF NOT APPROPRIATE

Investigator's Statement:

I \_\_\_\_\_

Confirm that I have carefully explained the nature, demands and any foreseeable risks (where applicable) of the proposed research to the participant.

Signed

Date